In [2]:
```python
import pandas as pd
import warnings
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
import seaborn as sns
from stargazer.stargazer import Stargazer
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
```

In [3]:
```python
data = pd.read_csv('kickers_v2.csv')
```

In [4]:
```python
data.head()
```

Out[4]:

	Unnamed: 0	Team	Year	GameMinute	Kicker	Distance	ScoreDiff	Grass	Success
0	1	PHI	2005	3	Akers	49	0	False	0
1	2	PHI	2005	29	Akers	49	-7	False	0
2	3	PHI	2005	51	Akers	44	-7	False	1
3	4	PHI	2005	14	Akers	43	14	True	0
4	5	PHI	2005	60	Akers	23	0	True	1

In [5]:
```python
# It's important we check for NAN before we start our analysis.
data.isnull().values.any()
```

Out[5]:
```
False
```

PSET 1 Econ 1042 Sports Economics

1. Question

1. What was the minimum distance of a field goal kicked in this sample? What was the maximum? Mean? Median!
2. Why isn't the minimum lower? (For those who are not familiar with football, please read about how field goal distance is measured and its relationship to where the ball is on the field.)
3. What special circumstances might explain the maximum? (Hint: football is a game with 4, 15-minute quarters. At the end of the second quarter there is a halftime break and possession is assigned based on the result of a first-half coin toss)

In [6]:
```python
print(f"The median distance of a field goal kicked was {np.median(data['Distance'])}")
data['Distance'].describe()
```

```
The median distance of a field goal kicked was 37.0
```

Out[6]:
```
count    11187.000000
mean        36.897381
std         10.173351
min         18.000000
25%         28.000000
50%         37.000000
75%         45.000000
max         76.000000
Name: Distance, dtype: float64
```

1. The minimum distance of a field goal kicked in the sample was 18.00 yards. The maximum was 76.00 yards and the median was 37.0 yards. The mean was 36.897 yards
2. The minimum is 17 yards. This makes sense since the endzone is 10yards, and the ball has to be kicked from 7 yards from the line of scrimmage. Hence 10 + 7 = 17.

In [7]:
```python
# Lets find out what play was kicked from 76 yards away?
max_yard = data.loc[data['Distance'] == 76.00]
max_yard
```

Out[7]:

	Unnamed: 0	Team	Year	GameMinute	Kicker	Distance	ScoreDiff	Grass	Success
3557	3558	OAK	2008	30	Janikowski	76	15	True	0

3. The 76 yards field goal attempt from Janikowski was in the last second of the second quarter (video: https://www.youtube.com/watch?v=X7BepDe6Zoc). It makes sense to kick if far into the opponents end zone, if in the first half your team had the ball. Since, then the opposing team will start from further away from the kickers endzone. It's like as if the special team does a punt.

2. Question

Over the entire sample what percentage of kicks from 40 to 45 yards were made? Kicks over 45 yards?

In [8]:
```python
sample_size = len(data)
# let's find the number of successful kicks from 40-45 yards
kicks_40_45 = data.loc[(data['Distance'] > 40) & (data['Distance'] < 45)]
# We find that 1325 kicks were made in that range
success_40_45 = kicks_40_45['Success'].value_counts()
# print(success_40_45)
ratio_success = success_40_45[1]/(success_40_45[0] + success_40_45[1])
ratio = (len(kicks_40_45)/sample_size) * 100
print(f'{ratio:.3f}% of Kicks were from between 40-45 yards')

# How many kicks were over 45 yards?
# kicks
```

```
11.844% of Kicks were from between 40-45 yards
```

In [9]:
```python
kicks_above_45 = data.loc[data['Distance'] > 45]
ratio_above_45 = (len(kicks_above_45)/sample_size) * 100
print(f'{ratio_above_45:.3f}% of Kicks were from between 40-45 yards')
```

```
24.439% of Kicks were from between 40-45 yards
```

3. Question

Was the make rate higher on grass or on turf? Is that difference statistically significant? Do you think this is the true effect of surface? Why or why not? (Answer this by doing an OLS regression. For the entire assignment, let's use the heteroskedasticity robust standard errors, r in stata or the equivalent in R)

Let's compute the difference using $\Delta = \bar{Y}_{grass} - \bar{Y}_{turf}$ we shall report standard errors as heteroscedasticity robust (HC2)

In [10]:
```python
# define response variable
# statsmodel requires us to add a column where each value is 1 in order to compute intercept
data['Intercept'] = 1
# Since we find no NAN in our column
print(data['Grass'].isnull().values.any())
# We can conver the 'bool' values for Grass to the datatype 'int'
data['Grass'] = data['Grass'].astype(int)
Y = data[['Success']]
X = data[['Grass', 'Intercept']]
mod = sm.OLS(Y, X)
res = mod.fit(cov_type='HC2')
print(res.summary())
```

```
False
                            OLS Regression Results
==============================================================================
Dep. Variable:                Success   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     7.500
Date:                Wed, 01 Feb 2023   Prob (F-statistic):            0.00618
Time:                        21:59:23   Log-Likelihood:                -4845.9
No. Observations:               11187   AIC:                             9696.
Df Residuals:                   11185   BIC:                             9710.
Df Model:                           1
Covariance Type:                  HC2
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Grass         -0.0193      0.007     -2.739      0.006      -0.033      -0.005
Intercept      0.8433      0.005    164.864      0.000       0.833       0.853
==============================================================================
Omnibus:                     3155.584   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6555.427
Skew:                          -1.781   Prob(JB):                         0.00
Kurtosis:                       4.175   Cond. No.                         2.75
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC2)
```

In [11]:
```python
# Let's also try the Sklearn Library
# We can also use the Sklearn Library to do an OLS regression, but I don't think it has a summary function.
X = data[['Grass']]
reg = LinearRegression(fit_intercept=True).fit(X,Y)
parameters = reg.get_params()
print(reg.coef_[0][0])
```

```
-0.019329247569502543
```

We find that the observed difference is statistically insignificant at the $\alpha = 0.05$ level. It seems as if the surface does not have an impact on the observed average success rates of field goal kicks.

4. Question

1. How is distance of attempt correlated with surface? What might explain this? (Coaches get to choose when to kick a field goal, one is never forced)
2. How is distance correlated with make percentage?

In [12]:
```python
# Let's calculate the correlation between the columns
corr_surface = data['Distance'].corr(data['Grass'])
corr_success = data['Distance'].corr(data['Success'])
print(corr_surface)
print(corr_success)
```

```
-0.002551996001227438
-0.33693399701495164
```

The correlation coefficient for distance and or Grass is -0.0025, basically negligible. The correlation coefficiecnt for distance and success rates is -0.3369, meaning as distance increases the success rate goes down.

5. Question

1. What is the formula for omitted variable bias?
2. Given (a) what should happen to the estimate of the effect of a kick being on grass when you add in distance? Verify this is true.

1. Ommitted variable bias arises when the regressor X is correlated with an omitted variable.

The formula for omitted variable bias is
$\hat{\beta}_{1,OLS} = \frac{Cov(y,x_1)}{Var(x_1)}$ 2. Since distance and grass are negatively correlated as well as distance and success rate our estimate from the short regression will be positively biased. Ultimately, revealing that kicking on grass is harder then on turf.

In [13]:
```python
Y = data[['Success']]
X = data[['Grass', 'Distance', 'Intercept']]
mod = sm.OLS(Y, X)
res = mod.fit(cov_type='HC2')
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                Success   R-squared:                       0.114
Model:                            OLS   Adj. R-squared:                  0.114
Method:                 Least Squares   F-statistic:                     695.7
Date:                Wed, 01 Feb 2023   Prob (F-statistic):          1.74e-285
Time:                        21:59:23   Log-Likelihood:                -4171.1
No. Observations:               11187   AIC:                             8348.
Df Residuals:                   11184   BIC:                             8370.
Df Model:                           2
Covariance Type:                  HC2
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Grass         -0.0200      0.007     -3.004      0.003      -0.033      -0.007
Distance      -0.0124      0.000    -37.218      0.000      -0.013      -0.012
Intercept      1.2999      0.011    115.413      0.000       1.278       1.322
==============================================================================
Omnibus:                     2395.590   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4232.201
Skew:                          -1.449   Prob(JB):                         0.00
Kurtosis:                       3.824   Cond. No.                         152.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC2)
```

In [14]:
```python
mod = smf.ols(formula='Success ~ Grass + Distance', data=data).fit(cov_type='HC2')
print(mod.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                Success   R-squared:                       0.114
Model:                            OLS   Adj. R-squared:                  0.114
Method:                 Least Squares   F-statistic:                     695.7
Date:                Wed, 01 Feb 2023   Prob (F-statistic):          1.74e-285
Time:                        21:59:23   Log-Likelihood:                -4171.1
No. Observations:               11187   AIC:                             8348.
Df Residuals:                   11184   BIC:                             8370.
Df Model:                           2
Covariance Type:                  HC2
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.2999      0.011    115.413      0.000       1.278       1.322
Grass         -0.0200      0.007     -3.004      0.003      -0.033      -0.007
Distance      -0.0124      0.000    -37.218      0.000      -0.013      -0.012
==============================================================================
Omnibus:                     2395.590   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4232.201
Skew:                          -1.449   Prob(JB):                         0.00
Kurtosis:                       3.824   Cond. No.                         152.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC2)
```

In [15]:
```python
data.columns
```

Out[15]:
```
Index(['Unnamed: 0', 'Team', 'Year', 'GameMinute', 'Kicker', 'Distance',
       'ScoreDiff', 'Grass', 'Success', 'Intercept'],
      dtype='object')
```

6. Question

1. Run an ols regression of kick success on distance, surface, point differential, and clock time. Interpret the coefficients. Does it seem like kickers do better or worse late in the game? Does the score of the game seem to effect them?
2. Now add in kicker fixed effects (i.kicker in Stata), what do these correct for? How does adjusted r-squared change?

In [16]:
```python
mod = smf.ols(formula='Success ~ Distance + Grass + ScoreDiff + GameMinute', data=data).fit(cov_type='HC2')
print(mod.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                Success   R-squared:                       0.114
Model:                            OLS   Adj. R-squared:                  0.114
Method:                 Least Squares   F-statistic:                     347.8
Date:                Wed, 01 Feb 2023   Prob (F-statistic):          1.07e-282
Time:                        21:59:23   Log-Likelihood:                -4171.0
No. Observations:               11187   AIC:                             8352.
Df Residuals:                   11182   BIC:                             8389.
Df Model:                           4
Covariance Type:                  HC2
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.2987      0.013    101.462      0.000       1.274       1.324
Distance      -0.0124      0.000    -37.158      0.000      -0.013      -0.012
Grass         -0.0200      0.007     -3.004      0.003      -0.033      -0.007
ScoreDiff     -0.0001      0.000     -0.285      0.776      -0.001       0.001
GameMinute  4.408e-05      0.000      0.221      0.825      -0.000       0.000
==============================================================================
Omnibus:                     2395.605   Durbin-Watson:                   1.981
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4232.237
Skew:                          -1.449   Prob(JB):                         0.00
Kurtosis:                       3.824   Cond. No.                         225.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC2)
```

1. The Game minute seems to have no statistically significant effect on Kicker performance. Furthermore, the point differential of the game does not seem to be statistically significant either, and also not affect kicker success rates.

In [17]:
```python
mod = smf.ols(formula='Success ~ Distance + Grass + ScoreDiff + GameMinute + C(Kicker)', data=data).fit(cov_typ
print(mod.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                Success   R-squared:                       0.127
Model:                            OLS   Adj. R-squared:                  0.121
Method:                 Least Squares   F-statistic:                 8.581e+10
Date:                Wed, 01 Feb 2023   Prob (F-statistic):               0.00
Time:                        21:59:23   Log-Likelihood:                -4088.0
No. Observations:               11187   AIC:                             8350.
Df Residuals:                   11100   BIC:                             8987.
Df Model:                          86
Covariance Type:                  HC2
===========================================================================================
                              coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------------
Intercept                   1.2659      0.024     53.087      0.000       1.219       1.313
C(Kicker)[T.Andersen]       0.0438      0.047      0.937      0.349      -0.048       0.136
C(Kicker)[T.Andrus]        -0.3664      0.216     -1.693      0.090      -0.791       0.058
C(Kicker)[T.Bailey]         0.1116      0.031      3.578      0.000       0.050       0.173
C(Kicker)[T.Barth]          0.0775      0.033      2.337      0.019       0.013       0.142
C(Kicker)[T.Bironas]        0.0760      0.029      2.668      0.008       0.020       0.132
C(Kicker)[T.Boswell]        0.1248      0.046      2.693      0.007       0.034       0.216
C(Kicker)[T.Brien]         -0.4597      0.275     -1.674      0.094      -0.998       0.079
C(Kicker)[T.Brindza]       -0.2372      0.153     -1.553      0.121      -0.537       0.062
C(Kicker)[T.Brown]          0.0311      0.026      1.188      0.235      -0.020       0.082
C(Kicker)[T.Bryant]         0.0572      0.028      2.079      0.038       0.003       0.111
C(Kicker)[T.Buehler]       -0.0320      0.078     -0.411      0.681      -0.184       0.120
C(Kicker)[T.Bullock]        0.0350      0.044      0.801      0.423      -0.051       0.121
C(Kicker)[T.Carney]         0.0037      0.035      0.105      0.916      -0.065       0.073
C(Kicker)[T.Carpenter]      0.0690      0.029      2.375      0.018       0.012       0.126
C(Kicker)[T.Catanzaro]      0.0925      0.040      2.292      0.022       0.013       0.172
C(Kicker)[T.Coons]          0.0628      0.055      1.150      0.250      -0.044       0.170
C(Kicker)[T.Cortez]        -0.1175      0.108     -1.085      0.278      -0.330       0.095
C(Kicker)[T.Coutu]         -0.7064      0.022    -32.777      0.000      -0.749      -0.664
C(Kicker)[T.Crosby]         0.0113      0.029      0.392      0.695      -0.045       0.068
C(Kicker)[T.Cundiff]       -0.0331      0.035     -0.943      0.346      -0.102       0.036
C(Kicker)[T.Dawson]         0.0607      0.027      2.220      0.026       0.007       0.114
C(Kicker)[T.Edinger]       -0.0719      0.079     -0.915      0.360      -0.226       0.082
C(Kicker)[T.Elam]           0.0350      0.035      1.004      0.315      -0.033       0.103
C(Kicker)[T.Elling]        -0.5950      0.023    -25.669      0.000      -0.640      -0.550
C(Kicker)[T.Feely]          0.0476      0.029      1.634      0.102      -0.010       0.105
C(Kicker)[T.Folk]           0.0112      0.031      0.363      0.717      -0.050       0.072
C(Kicker)[T.Forbath]        0.0543      0.045      1.213      0.225      -0.033       0.142
C(Kicker)[T.France]        -0.0472      0.134     -0.353      0.724      -0.309       0.215
C(Kicker)[T.Franks]         0.0361      0.091      0.398      0.691      -0.142       0.214
C(Kicker)[T.Freese]        -0.3562      0.159     -2.245      0.025      -0.667      -0.045
C(Kicker)[T.Gano]           0.0173      0.034      0.510      0.610      -0.049       0.084
C(Kicker)[T.Gostkowski]     0.0601      0.027      2.238      0.025       0.007       0.113
C(Kicker)[T.Gould]          0.0664      0.027      2.448      0.014       0.013       0.120
C(Kicker)[T.Graham]         0.0374      0.029      1.311      0.190      -0.019       0.093
C(Kicker)[T.Gramatica]      0.0166      0.083      0.200      0.842      -0.147       0.180
C(Kicker)[T.Hall]           0.0287      0.071      0.402      0.687      -0.111       0.168
C(Kicker)[T.Hanson]         0.0673      0.031      2.181      0.029       0.007       0.128
C(Kicker)[T.Hartley]        0.0105      0.041      0.257      0.797      -0.070       0.091
C(Kicker)[T.Hauschka]       0.0743      0.030      2.445      0.014       0.015       0.134
C(Kicker)[T.Henery]         0.0183      0.042      0.440      0.660      -0.063       0.100
C(Kicker)[T.Hocker]        -0.0916      0.118     -0.775      0.438      -0.323       0.140
C(Kicker)[T.Hopkins]        0.1042      0.056      1.861      0.063      -0.006       0.214
C(Kicker)[T.Janikowski]     0.0514      0.029      1.802      0.072      -0.005       0.107
C(Kicker)[T.Kaeding]        0.0432      0.031      1.396      0.163      -0.017       0.104
C(Kicker)[T.Kasay]          0.0653      0.030      2.186      0.029       0.007       0.124
C(Kicker)[T.Koenen]        -0.4115      0.137     -3.005      0.003      -0.680      -0.143
C(Kicker)[T.Lambo]          0.0743      0.067      1.101      0.271      -0.058       0.207
C(Kicker)[T.Lindell]        0.0325      0.030      1.086      0.277      -0.026       0.091
C(Kicker)[T.Longwell]       0.0408      0.032      1.268      0.205      -0.022       0.104
C(Kicker)[T.Mare]          -0.0100      0.033     -0.301      0.763      -0.075       0.055
C(Kicker)[T.McManus]        0.0631      0.049      1.295      0.195      -0.032       0.159
C(Kicker)[T.Medlock]       -0.1423      0.131     -1.083      0.279      -0.400       0.115
C(Kicker)[T.Mehlhaff]      -0.1027      0.264     -0.388      0.698      -0.621       0.416
C(Kicker)[T.Murray]         0.1003      0.086      1.165      0.244      -0.068       0.269
C(Kicker)[T.Myers]          0.0621      0.066      0.946      0.344      -0.067       0.191
C(Kicker)[T.Nedney]         0.0743      0.033      2.231      0.026       0.009       0.140
C(Kicker)[T.Novak]          0.0325      0.034      0.963      0.336      -0.034       0.099
C(Kicker)[T.Nugent]         0.0083      0.030      0.275      0.783      -0.051       0.068
C(Kicker)[T.Parkey]         0.0666      0.055      1.205      0.228      -0.042       0.175
C(Kicker)[T.Peterson]       0.0538      0.057      0.943      0.345      -0.058       0.165
C(Kicker)[T.Pettrey]       -0.4034      0.253     -1.597      0.110      -0.899       0.092
C(Kicker)[T.Potter]        -0.0665      0.203     -0.328      0.743      -0.465       0.331
C(Kicker)[T.Prater]         0.0531      0.031      1.718      0.086      -0.007       0.114
C(Kicker)[T.Rackers]        0.0531      0.029      1.801      0.072      -0.005       0.111
C(Kicker)[T.Rayner]        -0.0642      0.050     -1.293      0.196      -0.161       0.033
C(Kicker)[T.Reed]           0.0236      0.032      0.731      0.465      -0.040       0.087
C(Kicker)[T.Santos]         0.0574      0.045      1.283      0.200      -0.030       0.145
C(Kicker)[T.Schmitt]       -0.1605      0.368     -0.436      0.663      -0.881       0.560
C(Kicker)[T.Scifres]        0.2547      0.021     12.298      0.000       0.214       0.295
C(Kicker)[T.Scobee]         0.0329      0.030      1.088      0.277      -0.026       0.092
C(Kicker)[T.Stitser]       -0.0093      0.135     -0.068      0.946      -0.275       0.256
C(Kicker)[T.Stover]         0.0453      0.032      1.403      0.161      -0.018       0.109
C(Kicker)[T.Sturgis]        0.0080      0.044      0.180      0.857      -0.079       0.095
C(Kicker)[T.Succop]         0.0420      0.033      1.272      0.203      -0.023       0.107
C(Kicker)[T.Suisham]        0.0298      0.030      1.005      0.315      -0.028       0.088
C(Kicker)[T.Tucker]         0.1047      0.031      3.350      0.001       0.043       0.166
C(Kicker)[T.Tynes]         -0.0130      0.032     -0.408      0.683      -0.075       0.049
C(Kicker)[T.Vanderjagt]    -0.0203      0.058     -0.349      0.727      -0.134       0.094
C(Kicker)[T.Vinatieri]      0.0619      0.027      2.275      0.023       0.009       0.115
C(Kicker)[T.Walsh]          0.0711      0.035      2.031      0.042       0.002       0.140
C(Kicker)[T.Wilkins]        0.0438      0.042      1.043      0.297      -0.039       0.126
C(Kicker)[T.Zuerlein]       0.0277      0.041      0.681      0.496      -0.052       0.107
Distance                   -0.0125      0.000    -37.174      0.000      -0.013      -0.012
Grass                      -0.0246      0.007     -3.314      0.001      -0.039      -0.010
ScoreDiff               -3.034e-05      0.000     -0.083      0.934      -0.001       0.001
GameMinute               4.117e-05      0.000      0.207      0.836      -0.000       0.000
==============================================================================
Omnibus:                     2348.948   Durbin-Watson:                   2.007
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4107.577
Skew:                          -1.426   Prob(JB):                         0.00
Kurtosis:                       3.827   Cond. No.                     5.45e+03
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC2)
[2] The condition number is large, 5.45e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
/opt/homebrew/Caskroom/miniforge/base/envs/deep/lib/python3.10/site-packages/statsmodels/base/model.py:1871: Va
lueWarning: covariance of constraints does not have full rank. The number of constraints is 86, but rank is 85
  warnings.warn('covariance of constraints does not have full '
```

2. Adjusted R-square goes up, since we adjusting our regression for individuals attributes that do not vary over the time of a season.

7. Question

1. After you run the regression in part 6, do the command to predict fitted values from this regression: "predict, xb" in stata and equivalent in R "predict.lm". Based on this, what would you predict the probability of Justin Tucker cutting the lead to 8 (scorediff was -11) in 2015, when the gameminute was 30, and he was on turf
   A. We can't build a model using all inputs, and then try to predict sth when missing one value. Missing here is an input for the **Distance.** Hence we must find it ourselves in the data.
2. Does this estimate strike you as reasonable?
3. What would the estimate be for an average kicker?

In [18]:
```python
data_tucker = data.loc[data['Kicker'] == 'Tucker']
X = data_tucker[['Intercept', 'Distance', 'Grass', 'ScoreDiff', 'GameMinute']]
Y = data_tucker[['Success']]
reg_ols_tucker = sm.OLS(Y,X).fit(cov_type='HC2')
reg_ols_tucker.predict([1,30, False, -11, 30])
```

Out[18]:
```
array([0.93507468])
```

In [19]:
```python
# Let's use the Sklearn library for this prediction. Since we can specify the input.
# Since we are interested in Tucker
data_tucker = data.loc[data['Kicker'] == 'Tucker']
X = data_tucker[['Distance', 'Grass', 'ScoreDiff', 'GameMinute']]
Y = data_tucker[['Success']]
reg = LinearRegression(fit_intercept=True).fit(X,Y)
parameters = reg.get_params()
# Let's find the distance of the kick from tucker with scroediff -11, gameminute 30, and on turf
tucker = data_tucker.loc[(data_tucker['ScoreDiff']==-11)&(data_tucker['GameMinute']==30) & (data_tucker['Grass'
tucker

reg_coef = list(np.ravel(reg.coef_))
reg_coef.insert(0, 'Linear_Tucker')
proba = reg.predict([[30, False, -11, 30]])[0][0]
reg_coef.append(proba)
results = pd.DataFrame([reg_coef], columns=['Model', 'Distance', 'Grass', 'ScoreDiff', 'GameMinute', 'Proba'])
results
```

```
/opt/homebrew/Caskroom/miniforge/base/envs/deep/lib/python3.10/site-packages/sklearn/base.py:409: UserWarning:
X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
```

Out[19]:

	Model	Distance	Grass	ScoreDiff	GameMinute	Proba
0	Linear_Tucker	-0.012015	0.099391	0.000877	0.000754	0.935075

In [20]:
```python
# This is the play that the question is asking for
# We can ignore the warning message
tucker = [[30, False, -11, 30]]
print(reg.predict(tucker)[0][0])
```

```
0.9350746758606505
/opt/homebrew/Caskroom/miniforge/base/envs/deep/lib/python3.10/site-packages/sklearn/base.py:409: UserWarning:
X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
```

2. Let's see if this estimate seems reasonable for Tucker

In [21]:
```python
tucker_35_yards = data_tucker.loc[(data_tucker['Distance'] < 35)]
tucker_35_yards['Success'].value_counts()
```

Out[21]:
```
1    61
Name: Success, dtype: int64
```

In the sample Tucker made 61 kicks that were below 35 yards and he made every single one of them. Hence, the estimate in 1.) seems reasonable. On average in the sample we have 4765 observations of Kicks that were shot at less then 35 yard distance. Of those 0.947% were successful, hence the predicted probability seems to be a reasonable estimate.

In [22]:
```python
data_35_yards = data.loc[data['Distance'] < 35]
data_35_yards['Success'].value_counts()
```

Out[22]:
```
1    4513
0     252
Name: Success, dtype: int64
```

3. Let's predict the probability for an average kicker for that same shot.

In [23]:
```python
# using the Statsmodels library
X = data[['Intercept', 'Distance', 'Grass', 'ScoreDiff', 'GameMinute']]
Y = data[['Success']]
reg_ols = sm.OLS(Y,X).fit(cov_type='HC2')
reg_ols.predict([1,30, False, -11, 30])
```

Out[23]:
```
array([0.93001065])
```

In [24]:
```python
X = data[['Distance', 'Grass', 'ScoreDiff', 'GameMinute']]
Y = data[['Success']]
reg = LinearRegression(fit_intercept=True).fit(X,Y)
parameters = reg.get_params()
reg_coef = list(np.ravel(reg.coef_))
reg_coef.insert(0, 'Linear')
proba = reg.predict([[30, False, -11, 30]])[0][0]
reg_coef.append(proba)
results = pd.DataFrame([reg_coef], columns=['Model', 'Distance', 'Grass', 'ScoreDiff', 'GameMinute', 'Proba'])
results
```

```
/opt/homebrew/Caskroom/miniforge/base/envs/deep/lib/python3.10/site-packages/sklearn/base.py:409: UserWarning:
X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
```

Out[24]:

	Model	Distance	Grass	ScoreDiff	GameMinute	Proba
0	Linear	-0.012372	-0.019972	-0.000102	0.000044	0.930011

We estimate the probability for an average kicker to be 0.93%

---

8. Question

1. Now run a logistic regression with the same specification as in question 6. Use the command predict. Now what is the predicted probability of Tucker making that field goal? (the predict command in stata is now just "predict")
2. Why do the coefficients look so different for the logistic regression vs. OLS

In [25]:
```python
X = data[['Distance', 'Grass', 'ScoreDiff', 'GameMinute']]
Y = data['Success']
model_log = LogisticRegression(fit_intercept=True).fit(X,Y)
parameters = model_log.get_params()
pred = model_log.predict_proba([[30, False, -11, 30]])
model_log_coef = [list(np.ravel(model_log.coef_))]
print(f'We find the prediction for success to be {pred[0][1]}')
coef = pd.DataFrame(model_log_coef, columns=['Distance', 'Grass', 'ScoreDiff', 'GameMinute'])
coef
```

```
We find the prediction for success to be 0.9400478885815359
/opt/homebrew/Caskroom/miniforge/base/envs/deep/lib/python3.10/site-packages/sklearn/base.py:409: UserWarning:
X does not have valid feature names, but LogisticRegression was fitted with feature names
  warnings.warn(
```

Out[25]:

	Distance	Grass	ScoreDiff	GameMinute
0	-0.102842	-0.167622	-0.000962	0.000384

In [26]:
```python
# let's make it a bit prettier using the Stagazer library and the statsmodels package
X = data[['Intercept', 'Distance', 'Grass', 'ScoreDiff', 'GameMinute']]
log = sm.Logit(Y,X).fit()
pred = log.predict([1,30,False, -11, 30])
# print(log.predict([1, 30, False, -11, 30]))
# print(log.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.390574
         Iterations 7
```

In [27]:
```python
models = [reg_ols, log]
table = Stargazer(models)
table.custom_columns(['OLS Model', 'Logit Model'], [1, 1])
table.covariate_order(['Intercept', 'Distance', 'Grass', 'ScoreDiff', 'GameMinute'])
table
```

Out[27]:

	Dependent variable:Success	
	OLS Model	Logit Model
	(1)	(2)
Intercept	1.299^{***}	5.816^{***}
	(0.013)	(0.151)
Distance	-0.012^{***}	-0.103^{***}
	(0.000)	(0.003)
Grass	-0.020^{***}	-0.168^{***}
	(0.007)	(0.055)
ScoreDiff	-0.000	-0.001
	(0.000)	(0.003)
GameMinute	0.000	0.000
	(0.000)	(0.002)
Observations	11,187	11,187
R^2	0.114	
Adjusted R^2	0.114	
Residual Std. Error	0.351 (df=11182)	1.000 (df=11182)
F Statistic	347.846^{***} (df=4; 11182)	(df=4; 11182)
Note:	*p<0.1; **p<0.05; ***p<0.01	

2. Why do the coefficients look so different for the logistic regression vs. OLS

Inherently a logit model and an OLS model are two different models. The logit model uses a sigmoid function, whereas the OLS model uses a simple linear function. Naturally, we end up with different coefficient values.

---

9. Question

1. Who would you say was the best kicker in the NFL over this period? Why? Define best in at least two different ways. Try to quantify the size of the difference.
2. Are these differences stable over time? For example, if players switch team or year over year?

In [28]:
```python
data.loc[data['Kicker'] == 'Elling']
```

Out[28]:

	Unnamed: 0	Team	Year	GameMinute	Kicker	Distance	ScoreDiff	Grass	Success	Intercept
302	303	BAL	2005	30	Elling	54	-17	0	0	1

In [29]:
```python
# How do we define best kicker? A good kicker is one that makes most of the kicks?
# Let's try the approach where the best kicker is the most accurate e.g makes most of their Kicks regardless of

kicker_list = data['Kicker'].unique()

def data_per_kicker(kickers):
    accuracies = []
    for i in kickers:
        data_kicker = data.loc[data['Kicker'] == i]
        success = data_kicker['Success'].value_counts()
        try:
            accuracy = success[1]/(success[1] + success[0])
            accuracies.append({'Kicker' : i, 'Shots_taken': (success[1] + success[0]), 'Success': success[1], '
        except KeyError:
            accuracies.append({'Kicker': i, 'Accuracy' : np.nan})
    return accuracies

results = data_per_kicker(kicker_list)
frame = pd.DataFrame(results)
frame.sort_values(ascending=False, by='Accuracy')
```

Out[29]:

	Kicker	Shots_taken	Success	Accuracy
75	Boswell	39.0	36.0	0.923077
28	Peterson	25.0	23.0	0.920000
80	Hopkins	29.0	26.0	0.896552
58	Bailey	162.0	145.0	0.895062
69	Catanzaro	66.0	59.0	0.893939
...	...	...	...	...
21	Koenen	13.0	4.0	0.307692
2	Brien	4.0	1.0	0.250000
11	Elling	NaN	NaN	NaN
59	Coutu	NaN	NaN	NaN
61	Scifres	NaN	NaN	NaN

83 rows × 4 columns

According to this metric in our Sample Boswell was the most accurate Kicker. Then again we shall not forget that this is merely an average of all kicks, hence the value is hugely influenced, by how many kicks the respective Kicker did. Kickers such as Elling, Coutu, and Scifres had not 1 successful kick in our sample.

Let's try and quantify the best kicker in a new way. Let's look at accuracy rate when the $-4 < Score < 0$, meaning that the field goal could mean the change in winning vs losing team vs draw.

In [30]:
```python
# We use the same function as defined before.
kicker_list = data['Kicker'].unique()

def data_per_kicker(kickers):
    accuracies = []
    cond = (data['ScoreDiff']<0) & (data['ScoreDiff'] > - 4)
    for i in kickers:
        data_kicker = data.loc[(data['Kicker'] == i)]
        # For each kicker we only look at the shots they take that
        data_kicker = data_kicker.loc[(data_kicker['ScoreDiff'] < 0) & (data_kicker['ScoreDiff'] > - 4)]
        success = data_kicker['Success'].value_counts()
        try:
            accuracy = success[1]/(success[1] + success[0])
            accuracies.append({'Kicker' : i, 'Shots_taken_ScoreDiff': (success[1] + success[0]), 'Success_Score
        except KeyError:
            accuracies.append({'Kicker': i, 'Accuracy_ScoreDiff' : np.nan})
    return accuracies

results = data_per_kicker(kicker_list)
frame_2 = pd.DataFrame(results)

df = frame.merge(frame_2, on='Kicker')
df
```

Out[30]:

	Kicker	Shots_taken	Success	Accuracy	Shots_taken_ScoreDiff	Success_ScoreDiff	Accuracy_ScoreDiff
0	Akers	336.0	269.0	0.800595	34.0	31.0	0.911765
1	Bironas	283.0	242.0	0.855124	33.0	27.0	0.818182
2	Brien	4.0	1.0	0.250000	NaN	NaN	NaN
3	Brown	488.0	401.0	0.821721	64.0	53.0	0.828125
4	Bryant	308.0	265.0	0.860390	46.0	37.0	0.804348
...	...	...	...	...	...	...	...
78	Franks	16.0	13.0	0.812500	NaN	NaN	NaN
79	Hocker	14.0	10.0	0.714286	NaN	NaN	NaN
80	Hopkins	29.0	26.0	0.896552	NaN	NaN	NaN
81	Lambo	32.0	26.0	0.812500	6.0	5.0	0.833333
82	Myers	30.0	26.0	0.866667	7.0	6.0	0.857143

83 rows × 7 columns

In [31]:
```python
# We can now sort and try to find the Kicker who makes most of the shots when it matters the most
print(df['Accuracy_ScoreDiff'].isna().sum())
df.sort_values(ascending=False, by='Accuracy_ScoreDiff')
```

```
23
```

Out[31]:

	Kicker	Shots_taken	Success	Accuracy	Shots_taken_ScoreDiff	Success_ScoreDiff	Accuracy_ScoreDiff
23	Longwell	186.0	157.0	0.844086	16.0	15.0	0.937500
12	Feely	282.0	239.0	0.847518	31.0	29.0	0.935484
58	Bailey	162.0	145.0	0.895062	28.0	26.0	0.928571
25	Nedney	149.0	129.0	0.865772	13.0	12.0	0.923077
15	Graham	259.0	222.0	0.857143	25.0	23.0	0.920000
...	...	...	...	...	...	...	...
76	Brindza	12.0	6.0	0.500000	NaN	NaN	NaN
77	Coons	32.0	28.0	0.875000	NaN	NaN	NaN
78	Franks	16.0	13.0	0.812500	NaN	NaN	NaN
79	Hocker	14.0	10.0	0.714286	NaN	NaN	NaN
80	Hopkins	29.0	26.0	0.896552	NaN	NaN	NaN

83 rows × 7 columns

We find that Longwell made 15 out of 16 shots, that turned the game. We also find that there are 23 Kickers in our sample that did not make a Kick when there score difference was between -3 and 0. We also find that Boswell who was our previous best Kicker now to not be in the rankings since he didnt take a single kick when the Score was between -3 and 0.

In [32]:
```python
df.loc[df['Kicker'] == 'Boswell']
```

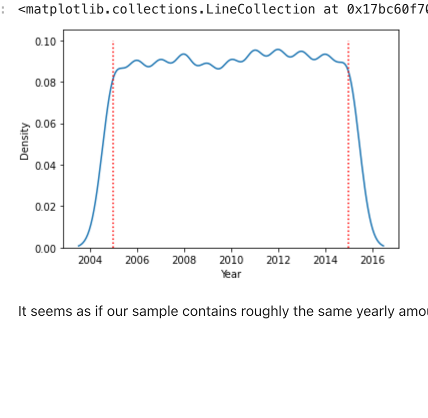
Out[32]:

	Kicker	Shots_taken	Success	Accuracy	Shots_taken_ScoreDiff	Success_ScoreDiff	Accuracy_ScoreDiff
75	Boswell	39.0	36.0	0.923077	NaN	NaN	NaN

Let's look at trends over time and more so if performance of kickers is persistent over time.

In [33]:
```python
# It makes sense to look at the distribution of observations per year to understand if we have an evenly distri
sns.kdeplot(data=data, x='Year')
plt.vlines(2005, 0 , 0.1, linestyles='dotted', color = 'r')
plt.vlines(2015, 0 , 0.1, linestyles='dotted', color = 'r')
```

Out[33]:
```
<matplotlib.collections.LineCollection at 0x17bc60f70>
```



It seems as if our sample contains roughly the same yearly amount of kicks between 2005 - 2015.

In [34]:
```python
# We use the same function as before but modify it to take into account years
# We use the same function as defined before.
kicker_list = data['Kicker'].unique()

def data_per_kicker(kickers):
    accuracies = []
    for i in kickers:
        # this is the dataframe for each kicker
        data_kicker = data.loc[(data['Kicker'] == i)]
        # For each kicker we only look at the shots they take that year
        years_played = data_kicker['Year'].unique()
        year = []
        for year in years_played:
            # this is the dataframe for each kicker for each year
            data_kicker_yearly = data_kicker.loc[(data['Year'] == year)]
            success = data_kicker_yearly['Success'].value_counts()
            if len(success) != 1:
                accuracy = success[1]/(success[1] + success[0])
                accuracies.append({'Year': year, 'Kicker' : i, 'Shots_taken': (success[1] + success[0]), 'Succe
            else:
                continue
    return accuracies

results = data_per_kicker(kicker_list)
frame_years = pd.DataFrame(results)
frame_years
```

Out[34]:

	Year	Kicker	Shots_taken	Success	Accuracy
0	2005	Akers	22	16	0.727273
1	2006	Akers	27	22	0.814815
2	2007	Akers	32	24	0.750000
3	2008	Akers	50	42	0.840000
4	2009	Akers	37	32	0.864865
...	...	...	...	...	...
390	2015	Franks	16	13	0.812500
391	2015	Hocker	14	10	0.714286
392	2015	Hopkins	29	26	0.896552
393	2015	Lambo	32	26	0.812500
394	2015	Myers	30	26	0.866667

395 rows × 5 columns

Since we can't plot all players. Let's create another table where we identify the players with the highest variance in accuracy(e.g. the least consistent) and those who have the lowest variance over the sample space.

For each kicker I calculate the variance $S^2 = \frac{\sum(x_i - \bar{x})^2}{n-1}$ where:

- x_i = the value of the observation
- $\bar{x}$ = the mean value of all observations
- n = the number of observations

In [35]:
```python
# we can use the var() to do this for us by specifiying the column
kickers_names = frame_years['Kicker'].unique()
results_var = []
for name in kickers_names:
    data = frame_years.loc[frame_years['Kicker'] == name]
    var = data.var(numeric_only='Float')
    results_var.append({'Kicker': name, 'Variance': var['Accuracy']})

results_var = pd.DataFrame(results_var)
results_var = results_var.sort_values(ascending=False, by='Variance').dropna()
# these are the 5 highest variance players
results_var.head()
```

Out[35]:

	Kicker	Variance
58	Henery	0.108169
44	Prater	0.043287
40	Gramatica	0.023802
48	Hauschka	0.021864
25	Novak	0.021560

In [36]:
```python
# these have the lowest variance
results_var.tail()
```

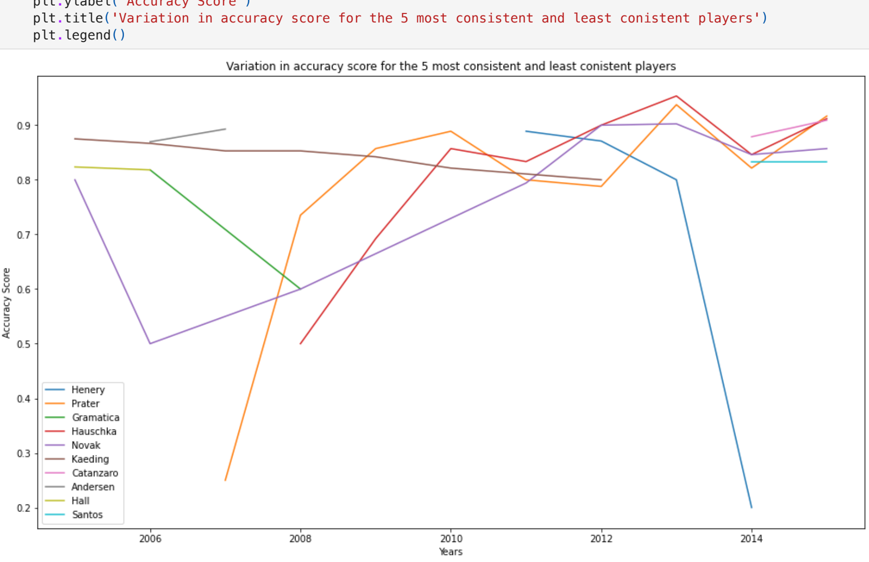
Out[36]:

	Kicker	Variance
18	Kaeding	0.000680
66	Catanzaro	0.000459
38	Andersen	0.000271
15	Hall	0.000014
71	Santos	0.000000

In [37]:
```python
# Let's grab the first 5 kickers and last 5 kickers to plot
kickers = list(results_var['Kicker'].unique())
kickers = kickers[:5] + kickers[-5:]

fig, axs = plt.subplots(1,1,figsize=(16,9))

for x in kickers:
    data = frame_years.loc[frame_years['Kicker'] == x]
    plt.plot(data['Year'], data['Accuracy'], label=f'{x}')
    plt.xlabel('Years')
    plt.ylabel('Accuracy Score')
    plt.title('Variation in accuracy score for the 5 most consistent and least conistent players')
    plt.legend()
```



Interestingly, we can observe that some players such as Hauschka improved thei kick accuracy year by year. This concludes question 9 part 2.

Question 10

10. Some argue that kickers get better with experience, in this dataset do you see evidence to support this conjecture? Try both a linear and quadratic specification. (For simplicity assume that there were no kicks attempted before the beginning of the dataset). What might be wrong with your estimates (besides incomplete data)? Explain!

We can answer this question by looking at the accuracies over time and whether this increases as experience goes up.

In [38]:
```python
# Let's compute experience in this dataset for each individual
frame_years['Exp'] = 0
names = frame_years['Kicker'].unique()
for i in names:
    frame_years.loc[(frame_years['Kicker'] == i), 'Exp'] = range(0, len(frame_years.loc[frame_years['Kicker'] =
```

In [39]:
```python
# Linear
data = frame_years.copy()
data['Intercept'] = 1
Y = data[['Accuracy']]
X = data[['Exp', 'Intercept']]
mod = sm.OLS(Y, X)
res = mod.fit(cov_type='HC2')
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Accuracy   R-squared:                       0.053
Model:                            OLS   Adj. R-squared:                  0.051
Method:                 Least Squares   F-statistic:                     21.84
Date:                Wed, 01 Feb 2023   Prob (F-statistic):           4.08e-06
Time:                        21:59:24   Log-Likelihood:                 342.44
No. Observations:                 395   AIC:                            -680.9
Df Residuals:                     393   BIC:                            -672.9
Df Model:                           1
Covariance Type:                  HC2
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Exp            0.0087      0.002      4.673      0.000       0.005       0.012
Intercept      0.7876      0.010     82.432      0.000       0.769       0.806
==============================================================================
Omnibus:                      208.795   Durbin-Watson:                   1.792
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1388.476
Skew:                          -2.196   Prob(JB):                    3.14e-302
Kurtosis:                      11.067   Cond. No.                         6.81
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC2)
```

In [40]:
```python
# Quadratic
# We need to use the Sklearn library for this
data = frame_years.copy()
data['Intercept'] = 1
Y = data[['Accuracy']]
X = np.array(data[['Exp']])
poly = PolynomialFeatures(degree=2, include_bias=False)
poly_features = poly.fit_transform(X.reshape(-1, 1))
reg = LinearRegression(fit_intercept=True).fit(poly_features, Y)
print(reg.coef_[0])
```

```
[ 0.01711115 -0.00103364]
```

Answer: I find that as experience goes up the accuracy of the players goes up as well. This estimate is rather small but statistically significant. Our estimate could be wrong, since some players might have gotten injured and hence were excluded from the experience category, but still continued learning about their game.

Question 11.

What are the omitted variables you would want in this dataset? List at least 3 and which direction the bias of excluding them could go and why.

I think it would be cool to look at factors such as age and also positional data. I know that there are datasets on Kaggle for example in the (NFL big data bowl competition) where movement(X, Y coordinates) as well as speed at relative times are recorded. I also think it would be interesting to see whether Kickers are better when their contracts are about to expire or whether that does not apply to Kickers. Excluding age could be a positive bias since, we could imagine that younger Kickers are more fit than older ones. On the other hand, we might discover that age is statistically insignificant.

In [ ]: