ABE 516X - Homework #4 - Linear Regression

The data I used for this assignment I found online and represents car sales for a variety of vehicles in a certain year. I wanted to look at how several different characteristics of the vehicle affected the retail price of the vehicle. After importing the data set I plotted several of the characteristics to see if there was a somewhat linear relationship. Of the ones that I plotted Engine size, engine horsepower and vehicle weight appeared to have the most linear relationships. I created linear models for these 3 metrics with regards to retail price. The plots for these can be found below. After creating the model and plotting it versus the data the summary statistics were calculated using the stat package. The best relationship was found between the horsepower and price with an R-squared value of 0.697.

In [2]:
```
# imports
import pandas as pd
import seaborn as sns
import statsmodels.formula.api as smf
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.model_selection import train_test_split
import numpy as np
import matplotlib.pyplot as plt

# allow plots to appear directly in the notebook
%matplotlib inline
```

In [3]:
```
# importing data
cars = pd.read_csv('cars.csv')
print(len(cars))
```

```
387
```

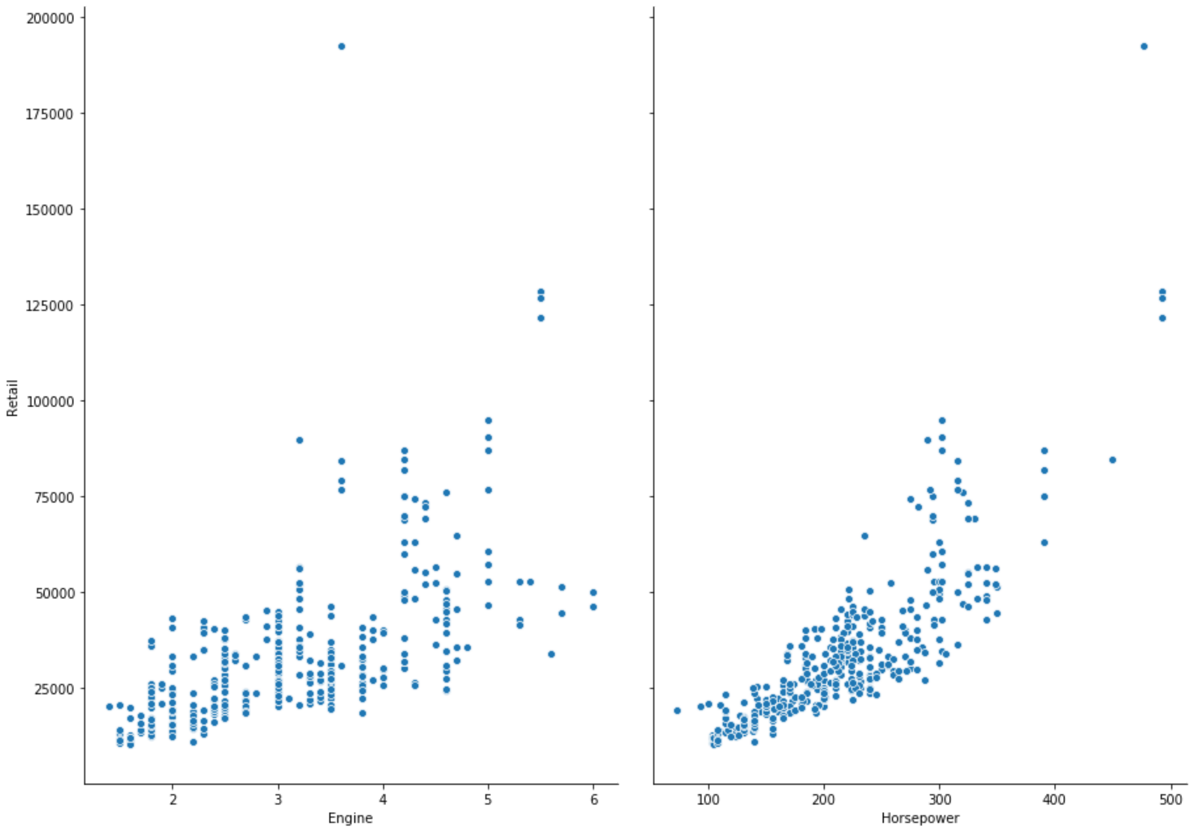
In [4]:
```
cars.head()
```

Out[4]:

	Unnamed: 0	AWD	RWD	Retail	Dealer	Engine	Cylinders	Horsepower	CityMPG	HighwayMP
0	Acura 3.5 RL	0	0	43755	39014	3.5	6	225	18	2
1	Acura 3.5 RL Navigation	0	0	46100	41100	3.5	6	225	18	2
2	Acura MDX	1	0	36945	33337	3.5	6	265	17	2
3	Acura NSX S	0	1	89765	79978	3.2	6	290	17	2
4	Acura RSX	0	0	23820	21761	2.0	4	200	24	3

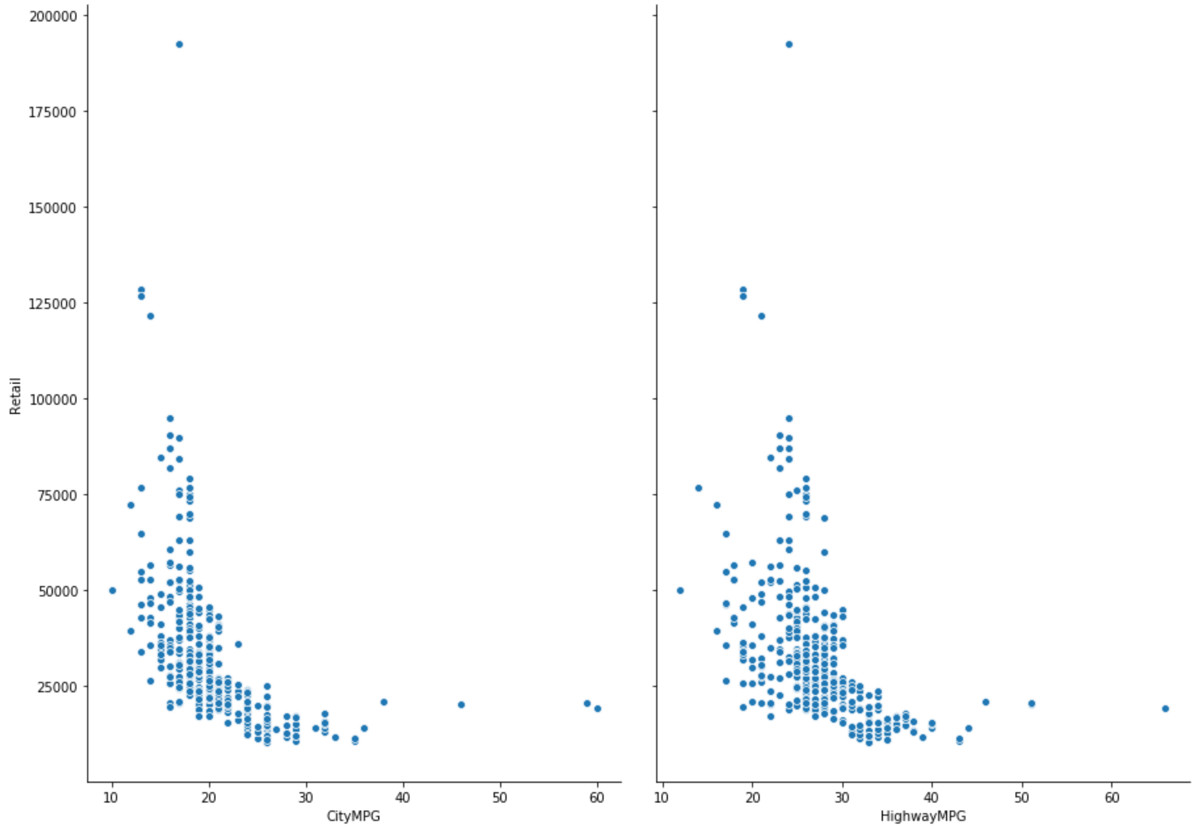
In [5]:
```
sns.pairplot(cars, x_vars=['Engine','Horsepower'], y_vars='Retail',height=9,as
pect=0.7)
```

Out[5]: <seaborn.axisgrid.PairGrid at 0x2ce7af5dc50>



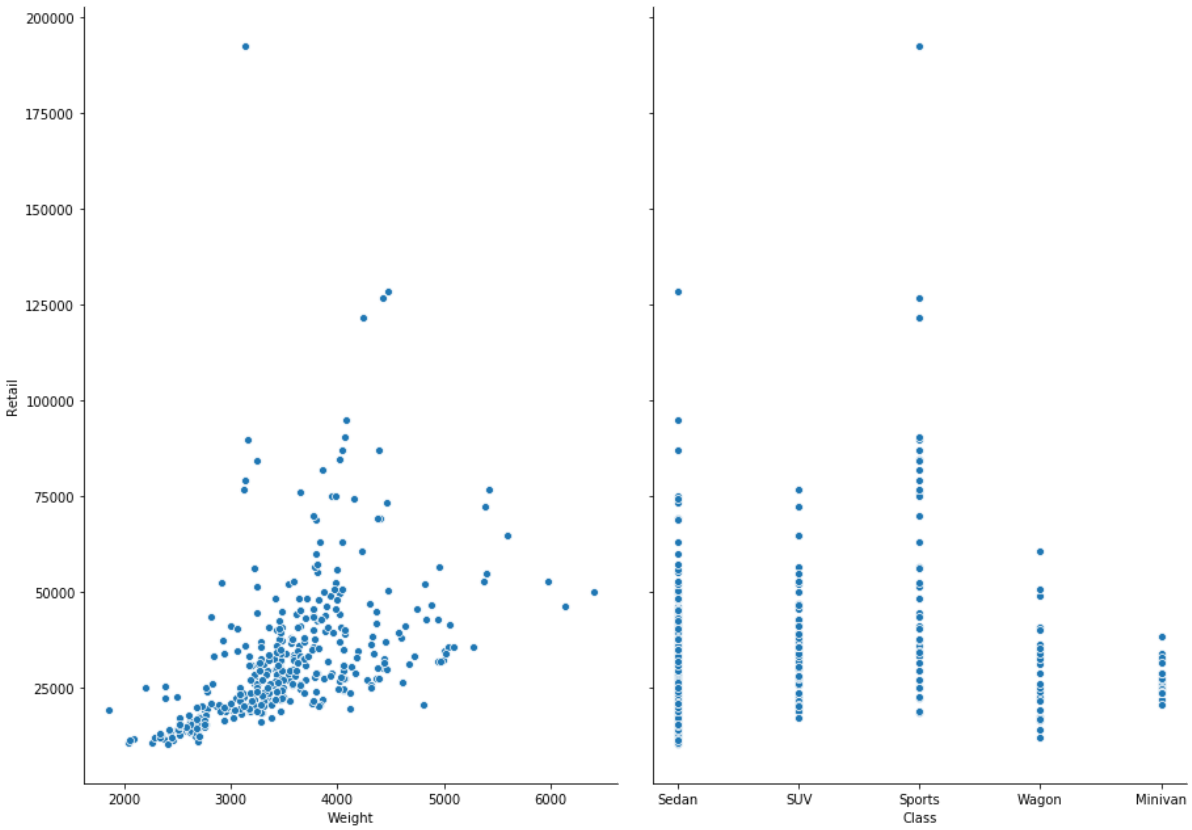
In [6]:
```
sns.pairplot(cars, x_vars=['CityMPG','HighwayMPG'], y_vars='Retail',height=9,a
spect=0.7)
```

Out[6]: <seaborn.axisgrid.PairGrid at 0x2ce7b568390>



In [7]:
```
sns.pairplot(cars, x_vars=['Weight','Class'], y_vars='Retail',height=9,aspect=0.7)
```

Out[7]: <seaborn.axisgrid.PairGrid at 0x2ce7baccbe0>



In [8]:
```
# Creating Variables for data that appeared linear
Price = cars['Retail']
Engine = cars['Engine']
HP = cars['Horsepower']
Weight = cars['Weight']
```

In [9]:
```
E_model = LinearRegression(fit_intercept=True)
HP_model = LinearRegression(fit_intercept=True)
W_model = LinearRegression(fit_intercept=True)
```

In [10]:
```
Engine_ = Engine[:,np.newaxis]
HP_ = HP[:,np.newaxis]
Weight_ = Weight[:,np.newaxis]
```

In [11]:
```
HP_.shape
```

Out[11]: (387, 1)

In [12]:
```
Engine_mod = E_model.fit(Engine_,Price)
HP_mod = HP_model.fit(HP_,Price)
Weight_mod = W_model.fit(Weight_,Price)
```

In [13]:
```
print(Engine_mod.coef_)
print(Engine_mod.intercept_)
print(HP_mod.coef_)
print(HP_mod.intercept_)
print(Weight_mod.coef_)
print(Weight_mod.intercept_)
```

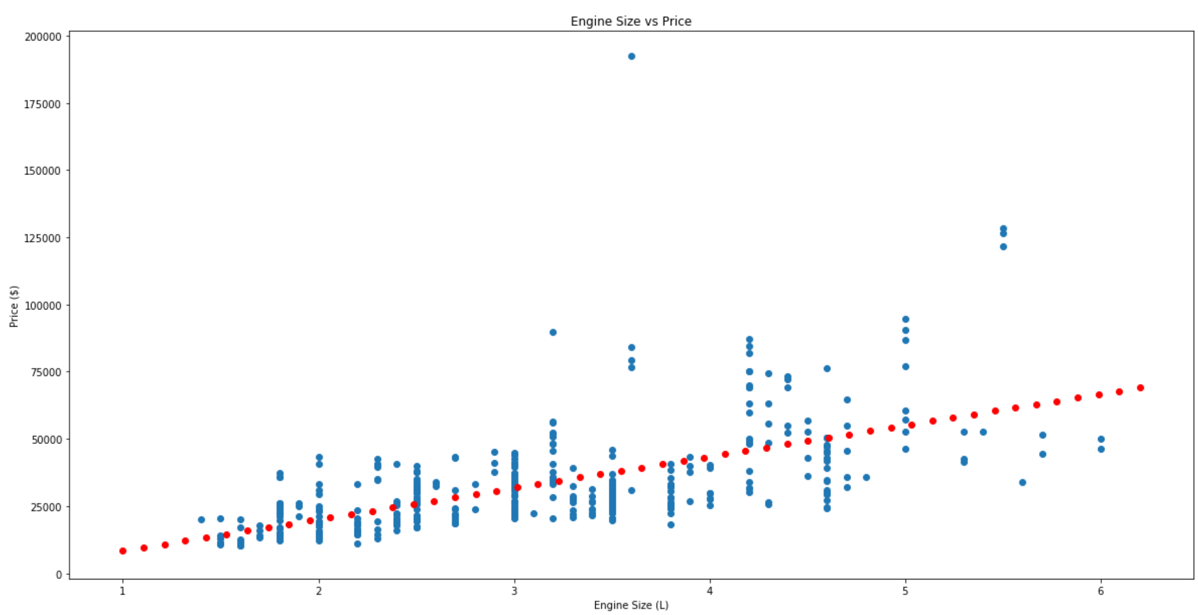
```
[11656.40973555]
-3222.960472689112
[234.42725402]
-17040.441372475398
[13.29852318]
-13745.285263114223
```

In [14]:
```
engine_fit = np.linspace(1,6.2)
engine_fit = engine_fit[:,np.newaxis]
hp_fit = np.linspace(70,500)
hp_fit = hp_fit[:,np.newaxis]
weight_fit = np.linspace(1750,6500)
weight_fit = weight_fit[:,np.newaxis]
```

In [15]:
```
engine_pred = Engine_mod.predict(engine_fit)
hp_pred = HP_mod.predict(hp_fit)
weight_pred = Weight_mod.predict(weight_fit)
```

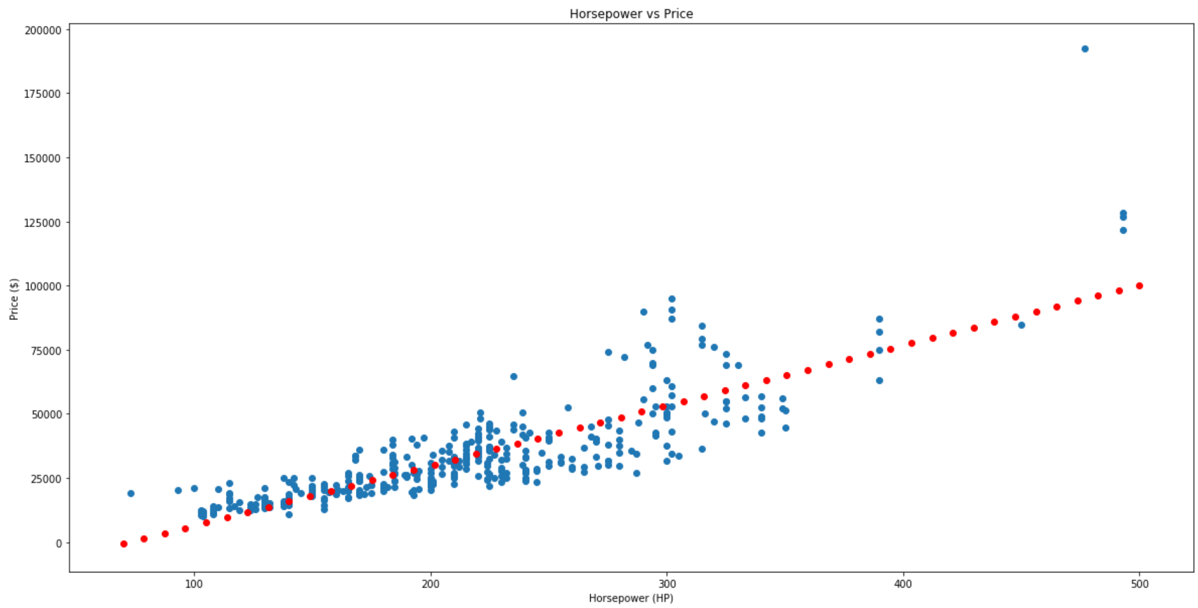
In [16]:
```
plt.figure(figsize=(20,10))
plt.scatter(Engine,Price)
plt.scatter(engine_fit,engine_pred,color='red')
plt.title('Engine Size vs Price')
plt.xlabel('Engine Size (L)')
plt.ylabel('Price ($)')
```

Out[16]: Text(0, 0.5, 'Price ($)')



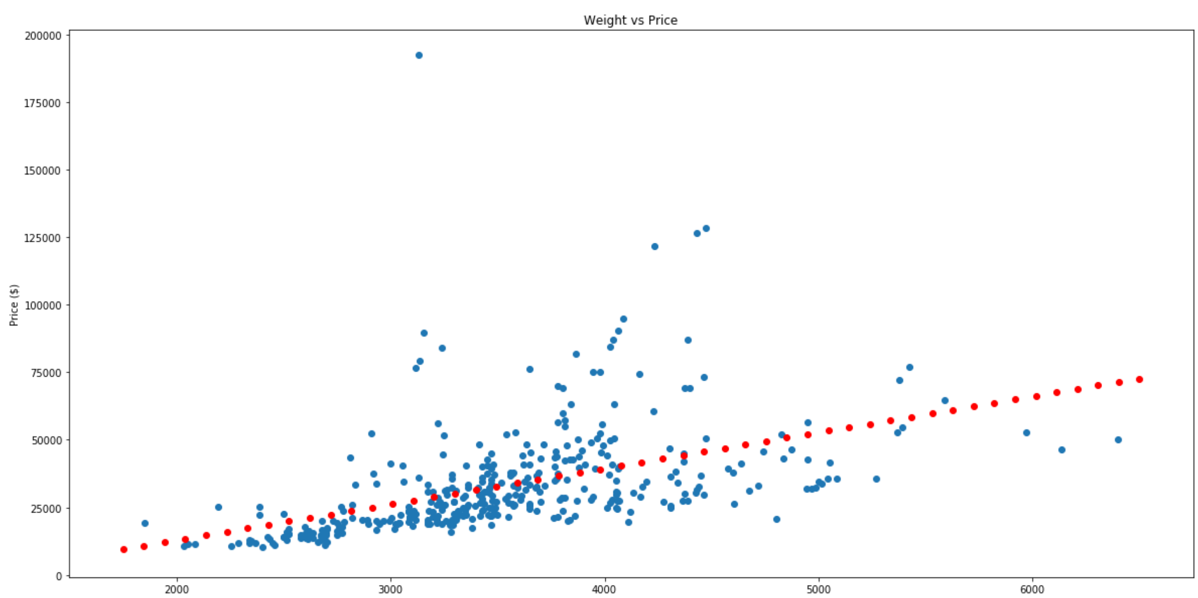
In [17]:
```
plt.figure(figsize=(20,10))
plt.scatter(HP,Price)
plt.scatter(hp_fit,hp_pred,color='red')
plt.title('Horsepower vs Price')
plt.xlabel('Horsepower (HP)')
plt.ylabel('Price ($)')
```

Out[17]: Text(0, 0.5, 'Price ($)')



In [18]:
```
plt.figure(figsize=(20,10))
plt.scatter(Weight,Price)
plt.scatter(weight_fit,weight_pred,color='red')
plt.title('Weight vs Price')
plt.xlabel('Weight (lbs)')
plt.ylabel('Price ($)')
```

Out[18]: Text(0, 0.5, 'Price ($)')



In [20]:
```
Engine_model_stat = smf.ols(formula='Retail ~ Engine', data=cars).fit()
print(Engine_model_stat.summary())
```

```
                            OLS Regression Results                            
==============================================================================
=
Dep. Variable:                 Retail   R-squared:                       0.35
9
Model:                            OLS   Adj. R-squared:                  0.35
8
Method:                 Least Squares   F-statistic:                     215.
9
Date:                Mon, 07 Oct 2019   Prob (F-statistic):           4.08e-3
9
Time:                        18:04:23   Log-Likelihood:                -4289.
8
No. Observations:                 387   AIC:                             858
4.
Df Residuals:                     385   BIC:                             859
1.
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Intercept  -3222.9605   2607.841     -1.236      0.217   -8350.353    1904.43
2
Engine      1.166e+04    793.293     14.694      0.000    1.01e+04    1.32e+0
4
==============================================================================
=
Omnibus:                      330.068   Durbin-Watson:                   0.86
8
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            10371.70
6
Skew:                           3.386   Prob(JB):                         0.0
0
Kurtosis:                      27.441   Cond. No.                         11.
6
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

In [21]:
```
HP_model_stat = smf.ols(formula='Retail ~ Horsepower', data=cars).fit()
print(HP_model_stat.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                 Retail   R-squared:                       0.69
7
Model:                            OLS   Adj. R-squared:                  0.69
7
Method:                 Least Squares   F-statistic:                     887.
1
Date:                Mon, 07 Oct 2019   Prob (F-statistic):           5.87e-10
2
Time:                        18:05:32   Log-Likelihood:                -4144.
6
No. Observations:                 387   AIC:                             829
3.
Df Residuals:                     385   BIC:                             830
1.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Intercept  -1.704e+04   1775.942     -9.595      0.000   -2.05e+04   -1.35e+0
4
Horsepower   234.4273      7.871     29.784      0.000     218.952     249.90
3
==============================================================================
=
Omnibus:                      256.354   Durbin-Watson:                   1.19
4
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5215.01
9
Skew:                           2.441   Prob(JB):                         0.0
0
Kurtosis:                      20.308   Cond. No.                         72
6.
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

In [22]:
```
Weight_model_stat = smf.ols(formula='Retail ~ Weight', data=cars).fit()
print(Weight_model_stat.summary())
```

```
                            OLS Regression Results                            
==============================================================================
=
Dep. Variable:                 Retail   R-squared:                       0.22
7
Model:                            OLS   Adj. R-squared:                  0.22
5
Method:                 Least Squares   F-statistic:                     112.
8
Date:                Mon, 07 Oct 2019   Prob (F-statistic):           2.81e-2
3
Time:                        18:05:54   Log-Likelihood:                -4326.
2
No. Observations:                 387   AIC:                            865
6.
Df Residuals:                     385   BIC:                            866
4.
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Intercept  -1.375e+04   4510.686     -3.047      0.002   -2.26e+04   -4876.62
2
Weight        13.2985      1.252     10.620      0.000      10.836      15.76
1
==============================================================================
=
Omnibus:                      350.543   Durbin-Watson:                   0.87
1
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            10423.49
0
Skew:                           3.760   Prob(JB):                         0.0
0
Kurtosis:                      27.287   Cond. No.                     1.84e+0
4
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 1.84e+04. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

In [ ]: