## Question 3 parts (b) through (h)

In [1]:
```
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import numpy as np
import re
```

In [2]:
```
# Load the CSV file into a DataFrame
import pandas as pd

df = pd.read_csv('auto.txt', sep='\t')

pd.set_option('display.max_rows', None)  # Display all rows
pd.set_option('display.max_columns', None)  # Display all columns

df.head()
```

Out[2]:

| | mpg | cylinders | displacement | horsepower | weight | acceleration | year | origin | name |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 18.0 8 307.0 130.0 3504. 12... | chevrolet chevelle malibu | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **1** | 15.0 8 350.0 165.0 3693. 11... | buick skylark 320 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2** | 18.0 8 318.0 150.0 3436. 11... | plymouth satellite | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **3** | 16.0 8 304.0 150.0 3433. 12... | amc rebel sst | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **4** | 17.0 8 302.0 140.0 3449. 10... | ford torino | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

**Reading the auto.txt file with relevant data cleaning steps, realised through hit-and-trial.**

In [3]:
```
file_path = 'auto.txt'

with open(file_path, 'r') as file:
    lines = file.readlines()

list_of_row_data = list()
columns_comma_separated = re.sub(r'\s+', ',', lines[0])
columns_list = columns_comma_separated.split(",")[:-1]

for line in lines[1:]:

    metrics = line.split("\t")[0]
    metrics_comma_separated_string = re.sub(r'\s+', ',', metrics)
    metrics_list = [float(value) if value!= "NA" else np.nan \
                    for value in metrics_comma_separated_string.split(",")]
    last_col = line.split("\t")[1]
```

```
    # print(metrics_list)
    # print(metrics)
    # print(last_col)

    metrics_list.append(last_col)
    list_of_row_data.append(metrics_list)


df = pd.DataFrame(list_of_row_data, columns=columns_list)
```

In [4]:
```
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
df.head()
```

Out[4]:

| | mpg | cylinders | displacement | horsepower | weight | acceleration | year | origin | nam |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 18.0 | 8.0 | 307.0 | 130.0 | 3504.0 | 12.0 | 70.0 | 1.0 | "chevrol chevel malibu"\ |
| **1** | 15.0 | 8.0 | 350.0 | 165.0 | 3693.0 | 11.5 | 70.0 | 1.0 | "buic skyla 320"\ |
| **2** | 18.0 | 8.0 | 318.0 | 150.0 | 3436.0 | 11.0 | 70.0 | 1.0 | "plymout satellite"\ |
| **3** | 16.0 | 8.0 | 304.0 | 150.0 | 3433.0 | 12.0 | 70.0 | 1.0 | "amc reb sst"\ |
| **4** | 17.0 | 8.0 | 302.0 | 140.0 | 3449.0 | 10.5 | 70.0 | 1.0 | "for torino"\ |

In [ ]:

In [ ]:

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
mpg             0
cylinders       0
displacement    0
horsepower      5
weight          0
acceleration    0
year            0
origin          0
name            0
dtype: int64
```

In [ ]:

In [6]:
```
# Create the derived variable year-squared
df['year_sq'] = df['year']**2
```

In [7]:
```
df[ [ "year", "year_sq"  ] ].head()
```

Out[7]:

| | year | year_sq |
|---|---|---|
| **0** | 70.0 | 4900.0 |
| **1** | 70.0 | 4900.0 |
| **2** | 70.0 | 4900.0 |
| **3** | 70.0 | 4900.0 |
| **4** | 70.0 | 4900.0 |

## Creating the uncentered regression model

In [8]:
```
X_0 = df[['year' , 'year_sq']]
y_0 = df['mpg']

# Add a constant, initialized to 1, to the predictor variables.
# This will be the intercept.
X_0 = sm.add_constant(X_0)
```

In [9]:
```
# Fit the linear regression model
model = sm.OLS(y_0, X_0).fit()

# Print the summary table of the regression model
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    mpg   R-squared:                       0.369
Model:                            OLS   Adj. R-squared:                  0.366
Method:                 Least Squares   F-statistic:                     115.4
Date:                Tue, 08 Oct 2024   Prob (F-statistic):           3.61e-40
Time:                        10:30:58   Log-Likelihood:                -1288.1
No. Observations:                 397   AIC:                             2582.
Df Residuals:                     394   BIC:                             2594.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        577.2523    146.671      3.936      0.000     288.896     865.609
year         -15.8409      3.865     -4.098      0.000     -23.440      -8.242
year_sq        0.1123      0.025      4.419      0.000       0.062       0.162
==============================================================================
Omnibus:                       21.346   Durbin-Watson:                   0.809
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               18.130
Skew:                           0.446   Prob(JB):                     0.000116
Kurtosis:                       2.450   Cond. No.                     2.73e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 2.73e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [ ]:

In [10]:
```
correlation_coefficient = df['year'].corr(df['year_sq'])
correlation_coefficient
```

Out[10]:
```
0.999759011614808
```

In [11]:
```
year_mean = np.mean(df['year'])
year_mean
```

Out[11]:
```
75.99496221662469
```

## Creating centered year

In [12]:
```
df['year_centered'] = df['year'] - year_mean
df['year_centered'].head()
```

Out[12]:
```
0   -5.994962
1   -5.994962
2   -5.994962
3   -5.994962
4   -5.994962
Name: year_centered, dtype: float64
```

In [ ]:

In [13]:
```
# Creating derived variable for centered year squared
df['year_centered_sq'] = df['year_centered']**2
df[ ['year_centered_sq', 'year_centered'] ].head()
```

Out[13]:

| | year_centered_sq | year_centered |
|---|---|---|
| **0** | 35.939572 | -5.994962 |
| **1** | 35.939572 | -5.994962 |
| **2** | 35.939572 | -5.994962 |
| **3** | 35.939572 | -5.994962 |
| **4** | 35.939572 | -5.994962 |

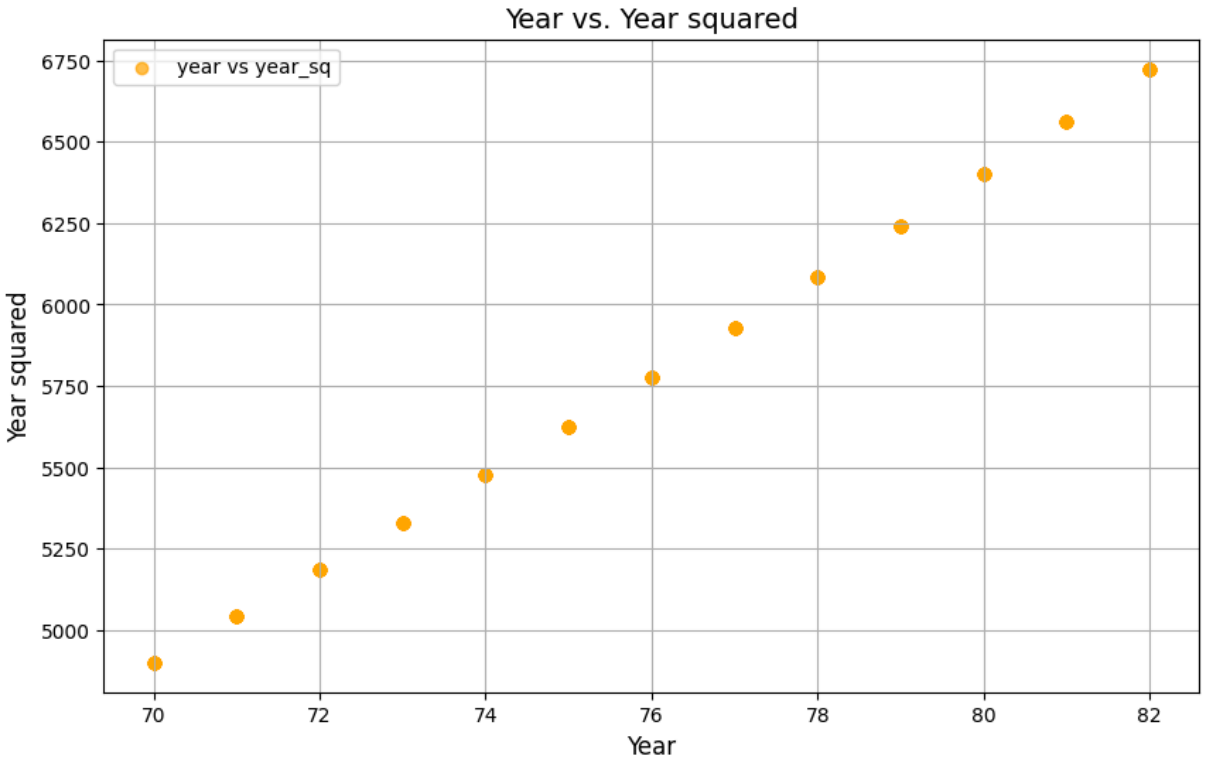
### Calculating correlation

In [14]:
```
correlation_coefficient = df['year_centered'].corr(df['year_centered_sq'])
correlation_coefficient
```

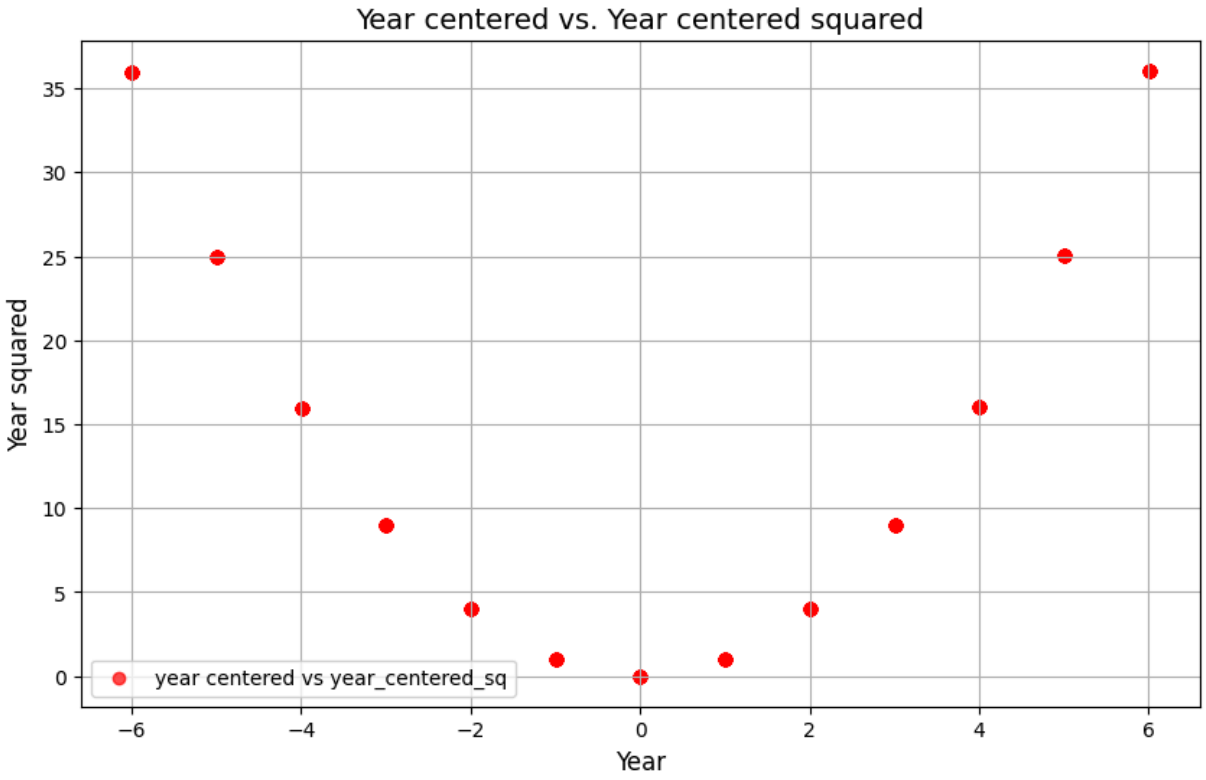
Out[14]:
```
0.014413995959565213
```

## Creating required scatter plots

In [15]:
```
plt.figure(figsize=(10, 6))
plt.scatter(df['year'], df['year_sq'], color='orange',
            label='year vs year_sq', alpha=0.7)
# plt.scatter(df['year_centere'], df['year_centered_sq'], color='orange', label='Ap
plt.title('Year vs. Year squared', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Year squared', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```




In [16]:
```
plt.figure(figsize=(10, 6))
plt.scatter(df['year_centered'], df['year_centered_sq'],
            color='red', label='year centered vs year_centered_sq',
            alpha=0.7)
# plt.scatter(df['year_centere'], df['year_centered_sq'], color='orange', label='Ap
plt.title('Year centered vs. Year centered squared', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Year squared', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```




## Creating the centered model

In [17]:
```
X_1 = df[['year_centered' , 'year_centered_sq']]
y_1 = df['mpg']

# Add a constant, initialized to 1, to the predictor variables.
# This will be the intercept.
X_1 = sm.add_constant(X_1)
```

In [ ]:
```
```

In [18]:
```
# Fit the linear regression model
model = sm.OLS(y_1, X_1).fit()

# Print the summary table of the regression model
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    mpg   R-squared:                       0.369
Model:                            OLS   Adj. R-squared:                  0.366
Method:                 Least Squares   F-statistic:                     115.4
Date:                Tue, 08 Oct 2024   Prob (F-statistic):           3.61e-40
Time:                        10:30:59   Log-Likelihood:                -1288.1
No. Observations:                 397   AIC:                             2582.
Df Residuals:                     394   BIC:                             2594.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         21.9906      0.466     47.214      0.000      21.075      22.906
year_centered  1.2278      0.085     14.469      0.000       1.061       1.395
year_centered_sq  0.1123      0.025      4.419      0.000       0.062       0.162
==============================================================================
Omnibus:                       21.346   Durbin-Watson:                   0.809
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               18.130
Skew:                           0.446   Prob(JB):                     0.000116
Kurtosis:                       2.450   Cond. No.                         27.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

In [ ]:

As can be observed ->

beta2 = gamma2 i.e. beta2 = 0.1123

evaluating ->

- beta1 = gamma1 - 2 * gamma2 * year_mean

---

gamma2 = 0.1123

gamma1 = 1.2278

year_mean = 75.99

In [19]:
```
gamma1 = 1.2278
gamma2 = 0.1123
year_mean = 75.99

# b2= gamma2
# b1 = gamma1 - 2*gamma2

beta2 = gamma1 - 2*gamma2*year_mean
print(beta2, round(beta2,2))
```

```
-15.839553999999998 -15.84
```

**As can be seen, the values derived for beta1 and beta2 in terms of gamma1 and gamma2 in the first part of the problem have been verified by the Betas and Gammas produced by the OLS models for un-centered and centered model.**

In [ ]:

In [ ]:

In [ ]:

In [ ]: