Task A

A1

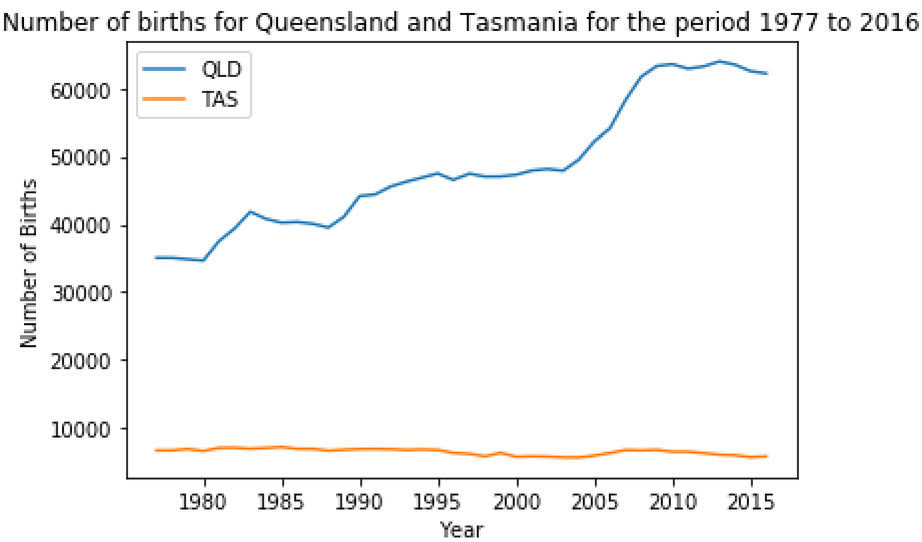
In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
from scipy.stats import linregress
```

A1.1.a

In [2]:

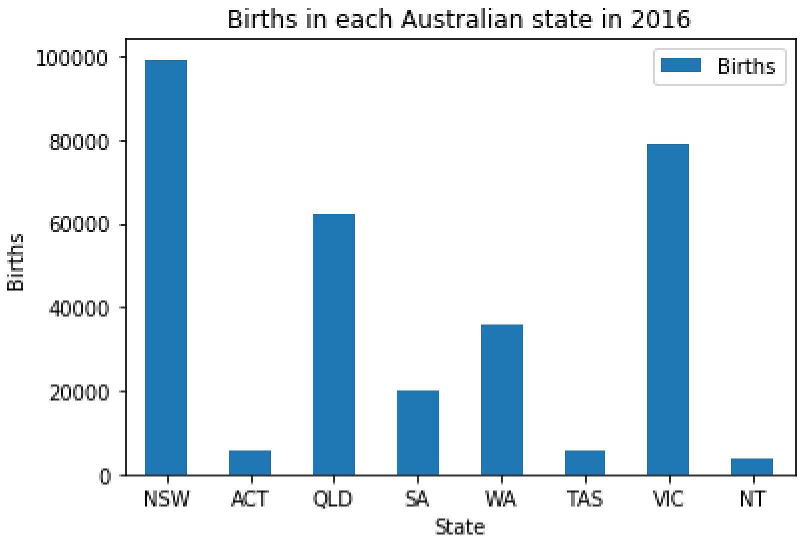
```
#1.a
births = pd.read_csv('Datasets/Task A/Births.csv')
plt.plot(births.Year, births.QLD, births.Year, births.TAS)
plt.xlabel('Year')
plt.ylabel('Number of Births')
plt.title('Number of births for Queensland and Tasmania for the period 1977 to 2
016')
plt.legend(['QLD','TAS'], loc='best')
plt.show()
```



A1.1.b

In [3]:

```
#1.b
condition1 = births['Year']==2016
q1b = births[condition1]
q1b = pd.melt(q1b, value_vars = ['NSW','ACT','QLD','SA','WA','TAS','VIC','NT'],
var_name = 'State')
q1b.rename(columns = {'value':'Births'}, inplace = True)
ax = q1b.plot.bar(x = 'State',y = 'Births', rot = 0, label = 'Births')
plt.title('Births in each Australian state in 2016')
plt.xlabel('State')
plt.ylabel('Births')
plt.show()
```



A1.2.a

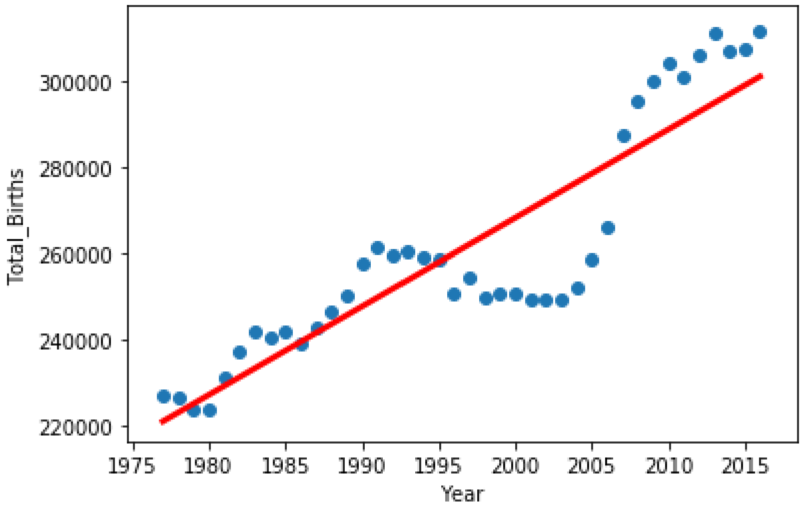
In [4]:

```
#2
q2 = pd.melt(births, id_vars = ['Year'], value_vars = ['NSW','ACT','QLD','SA','W
A','TAS','VIC','NT'], var_name = 'State')
q2.rename(columns = {'value': 'Births'}, inplace = True)
fun1 = {'Births':{'Total_Birth': 'sum'}}
q2 = q2.groupby('Year').agg(fun1)
q2 = q2.reset_index()
q2.columns = q2.columns.droplevel(0)
q2.rename(columns = {'':'Year'}, inplace = True)

#2.a

slope, intercept, r_value, p_value, std_err = linregress(q2['Year'],q2['Total_Bi
rth'])
line = [slope*xi + intercept for xi in q2['Year']]
plt.xlabel('Year')
plt.ylabel('Total_Births')
plt.plot(q2['Year'], line, 'r-', linewidth = 3)
plt.scatter(q2['Year'], q2['Total_Birth'])
plt.show()
```

```
/Users/linch/anaconda3/lib/python3.7/site-packages/pandas/core/group
by/generic.py:1315: FutureWarning: using a dict with renaming is dep
recated and will be removed in a future version
  return super(DataFrameGroupBy, self).aggregate(arg, *args, **kwarg
s)
```



A1.2.b

It looks not like a good fit because the regression is not so smooth, the period of 1995 to 2010 is in an unusual trend that going down obviously fraom 1995 to 2004 and going up rapidly from 2005 to 2010.

A1.2.c

In [5]:

```
#2.c
birth1 = int(slope * 2050 + intercept)
birth2 = int(slope * 2100 + intercept)
print(birth1,birth2)
```

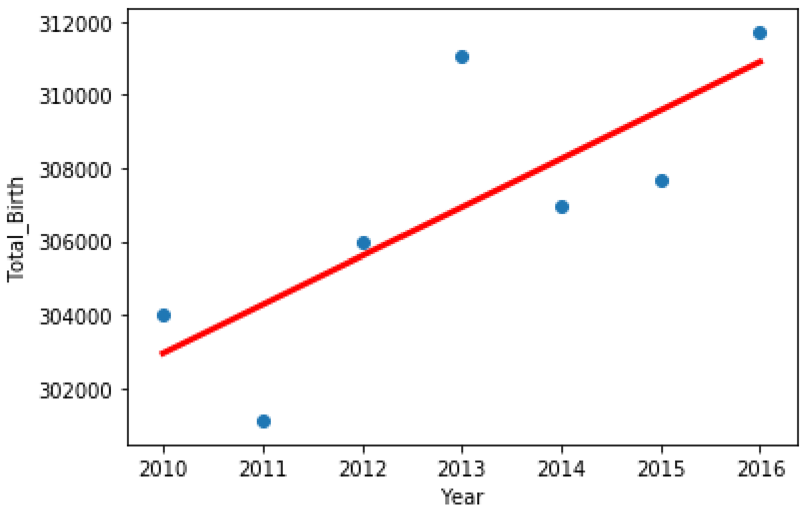
```
370945 473754
```

The predicted total births in Australia for the years 2050 and 2100 are 370945 and 473754

A1.2.d

In [6]:

```
#2.d
q2d = q2[q2.Year >= 2010]
slope, intercept, r_value, p_value, std_err = linregress(q2d['Year'],q2d['Total_
Birth'])
line = [slope*xi + intercept for xi in q2d['Year']]
plt.xlabel('Year')
plt.ylabel('Total_Birth')
plt.plot(q2d['Year'], line, 'r-', linewidth = 3)
plt.scatter(q2d['Year'], q2d['Total_Birth'])
plt.show()
```



The fit spread irregularly and sparsely. The graph in B2.a is better because the period is longer and the data of fit is much more than B2.d, so the linregress is more reasonable.

A1.2.e

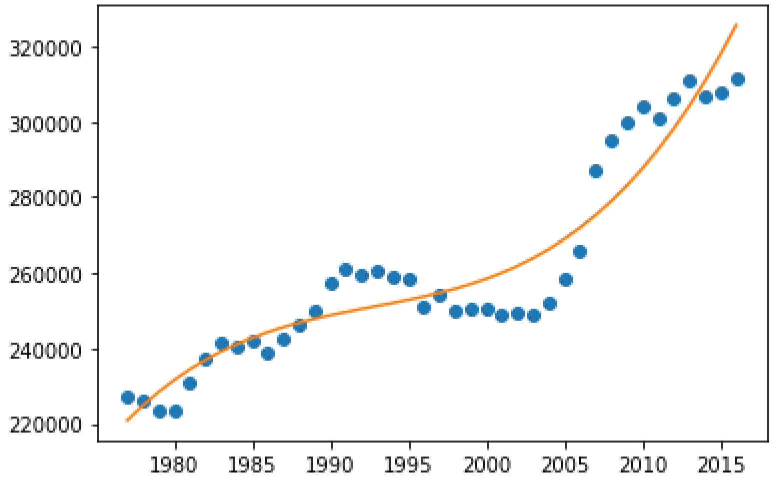
In [7]:

```
#2.e
import numpy as np

coef = np.polyfit(q2.Year, q2.Total_Birth, 3)
line = np.poly1d(coef)

plt.figure()
plt.plot(q2.Year, q2.Total_Birth, 'o', q2.Year, line(q2.Year))
plt.show()

birth2050 = int(line(2050))
birth2100 = int(line(2100))
print(birth2050, birth2100)
```




```
1137796 5872321
```

The polynomial graph suits the task better because the fit shows a trendency to be twisted and going up, a polynomial graph grows more nearly to the fit than in A2.a.

The predicted total births for 2050 and 2100 are 1137796 and 5872321

A1.3.a

In [8]:

```
#3.a
tfr = pd.read_csv('Datasets/Task A/TFR.csv')

q3 = pd.DataFrame(tfr, columns=['Year','QLD','NT'])
condition2 = q3['QLD']==q3['QLD'].min()
q3a = q3[condition2]
q3a
```

Out[8]:

	Year	QLD	NT
28	1999	1.8	2.123

The minimum value for TFR recorded in the dataset for QLD is 1.8 and it was in 1999, in the same year the TFR value for NT is 2.123

A1.4.a

In [9]:

```
#4.a
deaths = pd.read_csv('Datasets/Task A/Deaths.csv')
q4 = pd.melt(deaths, id_vars = ['Year'], value_vars = ['NSW','ACT','QLD','SA','W
A','TAS','VIC','NT'], var_name = 'State')
q4.rename(columns = {'value': 'Deaths'}, inplace = True)
fun1 = {'Deaths':{'Total Death': 'sum'}}
q4 = q4.groupby('Year').agg(fun1)
q4 = q4.reset_index()
q4.columns = q4.columns.droplevel(0)
q4.rename(columns = {'':'Year'}, inplace = True)

q4a = pd.merge(q2,q4, on=['Year'])
q4a
```

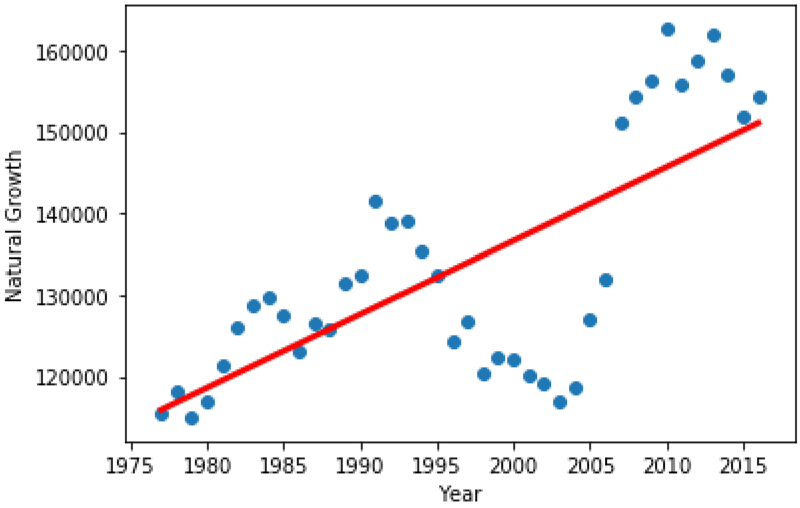
Out[9]:

	Year	Total_Birth	Total Death
0	1977	226954	111490
1	1978	226359	108059
2	1979	223370	108315
3	1980	223664	106654
4	1981	230920	109429
5	1982	237076	110990
6	1983	241764	112918
7	1984	240544	110887
8	1985	241814	114197
9	1986	239115	116069
10	1987	242797	116139
11	1988	246200	120463
12	1989	250155	118767
13	1990	257521	125112
14	1991	261158	119572
15	1992	259653	120836
16	1993	260494	121338
17	1994	258819	123491
18	1995	258561	126221
19	1996	250842	126392
20	1997	254146	127291
21	1998	249749	129252
22	1999	250687	128269
23	2000	250424	128386
24	2001	249175	128908
25	2002	249339	130246
26	2003	249107	132232
27	2004	252024	133225
28	2005	258321	131342
29	2006	265991	134038
30	2007	287178	135968
31	2008	295137	140728
32	2009	300055	143726
33	2010	303995	141441
34	2011	301133	145432
35	2012	305987	147195

	Year	Total_Birth	Total Death
36	2013	311091	149163
37	2014	306963	150013
38	2015	307649	155893
39	2016	311695	157363

In [10]:

```
slope, intercept, r_value, p_value, std_err = linregress(q4a['Year'],q4a['Total_
Birth']-q4a['Total Death'])
line = [slope*xi + intercept for xi in q4a['Year']]
plt.xlabel('Year')
plt.ylabel('Natural Growth')
plt.plot(q4a['Year'], line, 'r-', linewidth = 3)
plt.scatter(q4a['Year'], q4a['Total_Birth']-q4a['Total Death'])
plt.show()
```

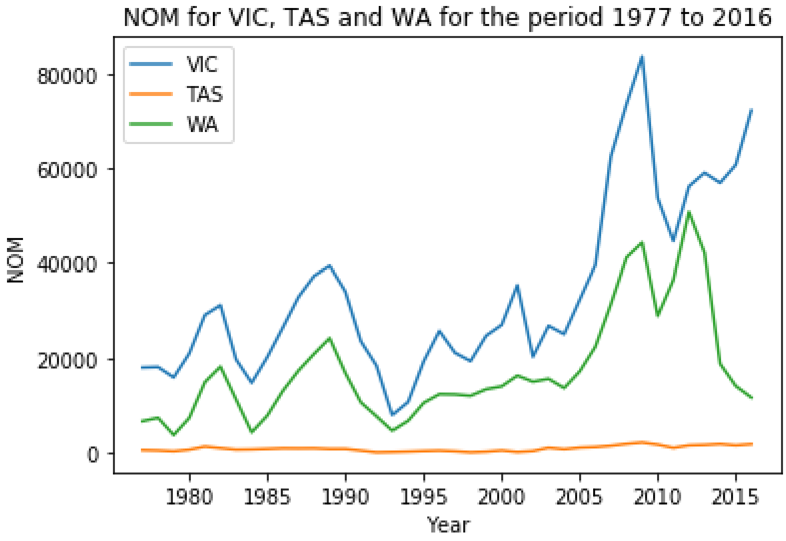


A2

A2.1.a

In [11]:

```
#1.a
nom = pd.read_csv('Datasets/Task A/NOM.csv')
plt.plot(nom.Year, nom.VIC, nom.Year, nom.TAS, nom.Year, nom.WA)
plt.xlabel('Year')
plt.ylabel('NOM')
plt.title('NOM for VIC, TAS and WA for the period 1977 to 2016')
plt.legend(['VIC','TAS','WA'], loc='best')
plt.show()
```

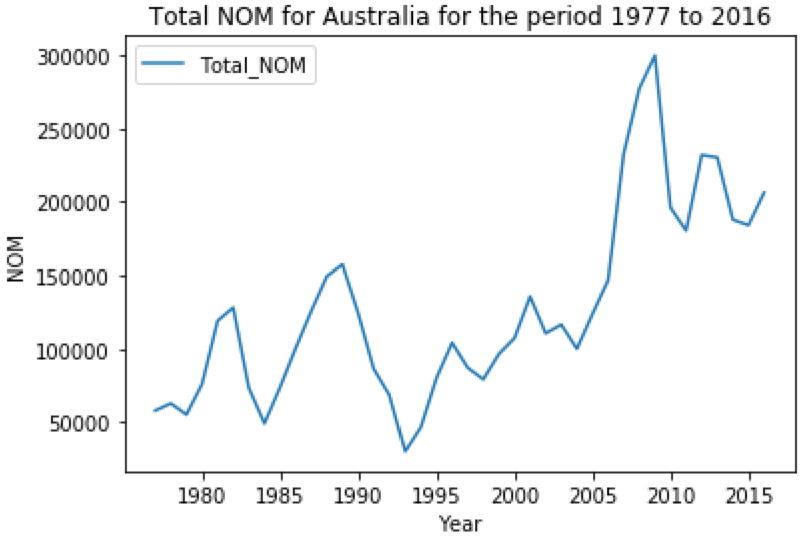


The trend for VIC is alternately going up, the trend for TAS is alternately going up and finally going down, the trend for WA is keeping near 0.

A2.1.b

In [12]:

```
#1.b
a1b = pd.melt(nom, id_vars=['Year'], value_vars=['NSW','ACT','QLD','SA','WA','TA
S','VIC','NT'], var_name=['State'])
a1b.rename(columns = {'value': 'NOM'},inplace = True)
fun1 = {'NOM':{'Total_NOM': 'sum'}}
a1b = a1b.groupby('Year').agg(fun1)
a1b = a1b.reset_index()
a1b.columns = a1b.columns.droplevel(0)
a1b.rename(columns = {'':'Year'}, inplace = True)
plt.plot(a1b.Year, a1b.Total_NOM)
plt.xlabel('Year')
plt.ylabel('NOM')
plt.title('Total NOM for Australia for the period 1977 to 2016')
plt.legend(['Total_NOM'], loc='best')
plt.show()
```



This trend is strange because the increase and decrease are both rapidly during 1977 to 2016.

A2.2.a

In [13]:

```
#2.a
nim = pd.read_csv('Datasets/Task A/NIM.csv')

nom1 = pd.melt(nom, id_vars = ['Year'], value_vars = ['NSW','VIC','QLD','SA','W
A','TAS','NT','ACT'], var_name = 'State')
nom1.rename(columns = {'value': 'NOM'}, inplace = True)

nim1 = pd.melt(nim, id_vars = ['Year'], value_vars = ['NSW','VIC','QLD','SA','W
A','TAS','NT','ACT'], var_name = 'State')
nim1.rename(columns = {'value': 'NIM'}, inplace = True)

q2a = pd.merge(nom1,nim1, on=['Year','State'])
q2a
#First year is 1977 and last year is 2016
```

Out[13]:

	Year	State	NOM	NIM
0	1977	NSW	25236	-9000
1	1978	NSW	25825	-2000
2	1979	NSW	28086	1500
3	1980	NSW	33499	-2000
4	1981	NSW	47291	-14963
5	1982	NSW	49393	-19584
6	1983	NSW	25740	-17181
7	1984	NSW	20698	-10267
8	1985	NSW	31279	-9328
9	1986	NSW	40922	-12462
10	1987	NSW	52693	-9524
11	1988	NSW	61490	-13340
12	1989	NSW	62636	-37974
13	1990	NSW	52199	-35983
14	1991	NSW	36496	-17206
15	1992	NSW	31178	-13807
16	1993	NSW	12628	-17535
17	1994	NSW	21929	-12180
18	1995	NSW	35952	-13478
19	1996	NSW	48045	-14770
20	1997	NSW	37291	-10661
21	1998	NSW	31843	-12249
22	1999	NSW	41088	-13050
23	2000	NSW	43689	-14274
24	2001	NSW	58619	-16315
25	2002	NSW	44411	-25102
26	2003	NSW	40919	-32467
27	2004	NSW	29820	-31098
28	2005	NSW	35205	-26321
29	2006	NSW	38523	-25576
...	...	...	...	...
290	1987	ACT	1624	1940
291	1988	ACT	1442	2062
292	1989	ACT	1080	-114
293	1990	ACT	1015	1330
294	1991	ACT	427	2932

	Year	State	NOM	NIM
295	1992	ACT	28	1365
296	1993	ACT	-603	1316
297	1994	ACT	-418	-426
298	1995	ACT	130	-486
299	1996	ACT	390	-656
300	1997	ACT	-70	-2470
301	1998	ACT	-242	-1982
302	1999	ACT	-225	-506
303	2000	ACT	-99	-91
304	2001	ACT	719	407
305	2002	ACT	698	-197
306	2003	ACT	885	-802
307	2004	ACT	456	-1586
308	2005	ACT	486	-842
309	2006	ACT	501	258
310	2007	ACT	1936	2465
311	2008	ACT	2518	260
312	2009	ACT	3608	-309
313	2010	ACT	3085	427
314	2011	ACT	1738	1354
315	2012	ACT	4019	1145
316	2013	ACT	2915	202
317	2014	ACT	2715	-812
318	2015	ACT	3496	-103
319	2016	ACT	3330	383

320 rows × 4 columns

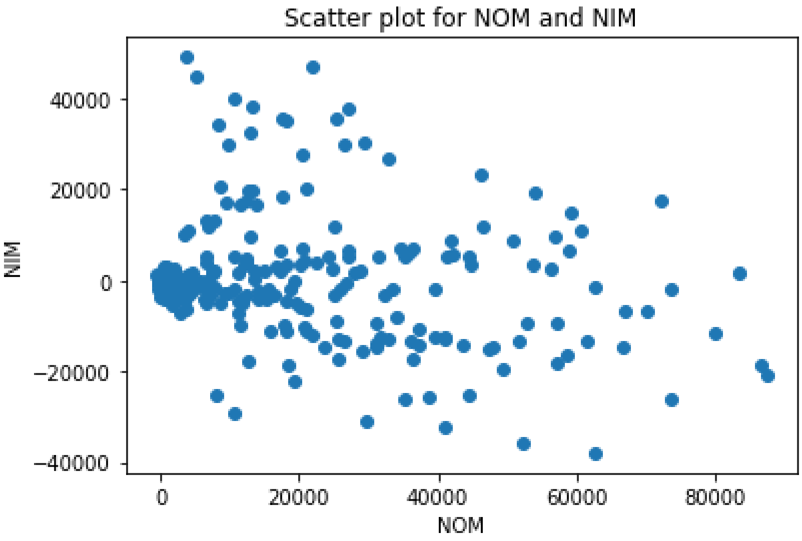
First year is 1977 and last year is 2016

A2.2.b

In [14]:

```
#2.b

plt.figure()
plt.scatter(q2a.NOM, q2a.NIM)
plt.title('Scatter plot for NOM and NIM')
plt.xlabel('NOM')
plt.ylabel('NIM')
plt.show()
```



Most of the values of NOM are around 0 in NIM.

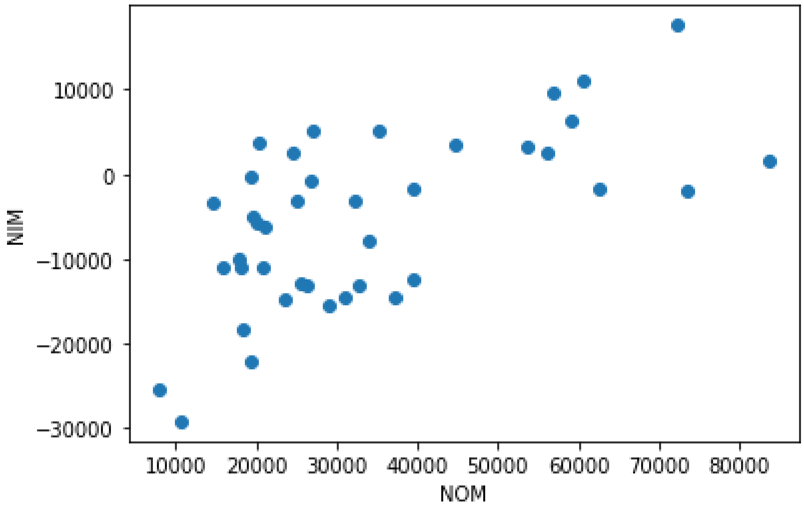
A2.2.c

In [15]:

```
#2.c
q2c = q2a[q2a.State == 'VIC']

plt.figure()
plt.scatter(q2c.NOM, q2c.NIM)
plt.xlabel('NOM')
plt.ylabel('NIM')

plt.show()
```

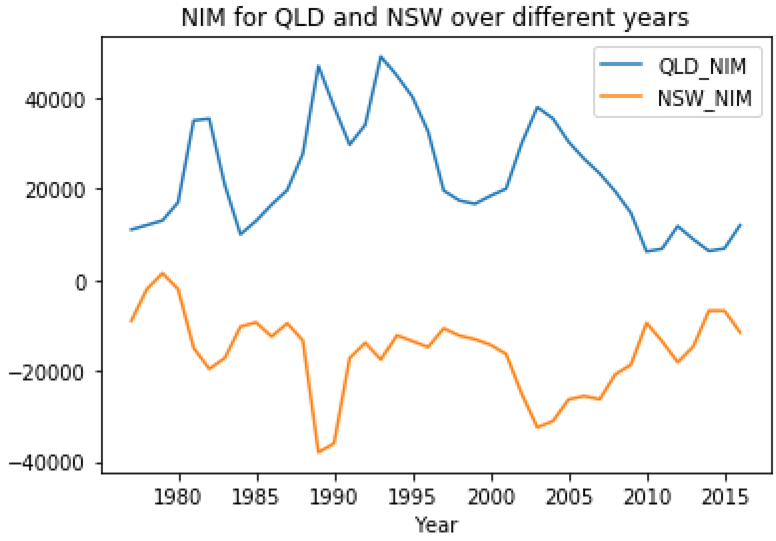


From the data of VIC, the NIM increases while NOM increasing.

A2.2.d

In [16]:

```
#2.d
plt.plot(nim.Year, nim.QLD, nim.Year, nim.NSW)
plt.xlabel('Year')
plt.title('NIM for QLD and NSW over different years')
plt.legend(['QLD_NIM','NSW_NIM'], loc='best')
plt.show()
```



The NIM for QLD and NSW have nearly opposite trends

A3

In [17]:

```
mNom = nom.melt(id_vars ='Year', var_name ='State', value_name='NOM')
mNim = nim.melt(id_vars ='Year', var_name ='State', value_name='NIM')
mBirth = births.melt(id_vars ='Year', var_name ='State', value_name='Birth')
mDeath = deaths.melt(id_vars ='Year', var_name ='State', value_name='Death')
mTfr = tfr.melt(id_vars ='Year', var_name ='State', value_name='TFR')

a3 = mNom.merge(mNim, on = ['Year', 'State'])
a3 = a3.merge(mBirth, on = ['Year', 'State'])
a3 = a3.merge(mDeath, on = ['Year', 'State'])
a3 = a3.merge(mTfr, on = ['Year', 'State'])

tpg = a3.Birth - a3.Death + a3.NOM + a3.NIM
a3['Total_Population_Growth'] = tpg
a3.head()
```

Out[17]:

	Year	State	NOM	NIM	Birth	Death	TFR	Total_Population_Growth
0	1977	NSW	25236	-9000	78173	42075	1.995	52334
1	1978	NSW	25825	-2000	78190	40121	1.953	61894
2	1979	NSW	28086	1500	77669	39975	1.902	67280
3	1980	NSW	33499	-2000	78859	39799	1.925	70559
4	1981	NSW	47291	-14963	80980	39979	1.942	73329

A3.1

In [18]:

```
#A3.1

from motionchart.motionchart import MotionChart

mchart = MotionChart(df = a3, key='Year', x='NOM', y='NIM', size='Total_Populati
on_Growth', category='State')
mchart.to_notebook()
```

A3.2.a

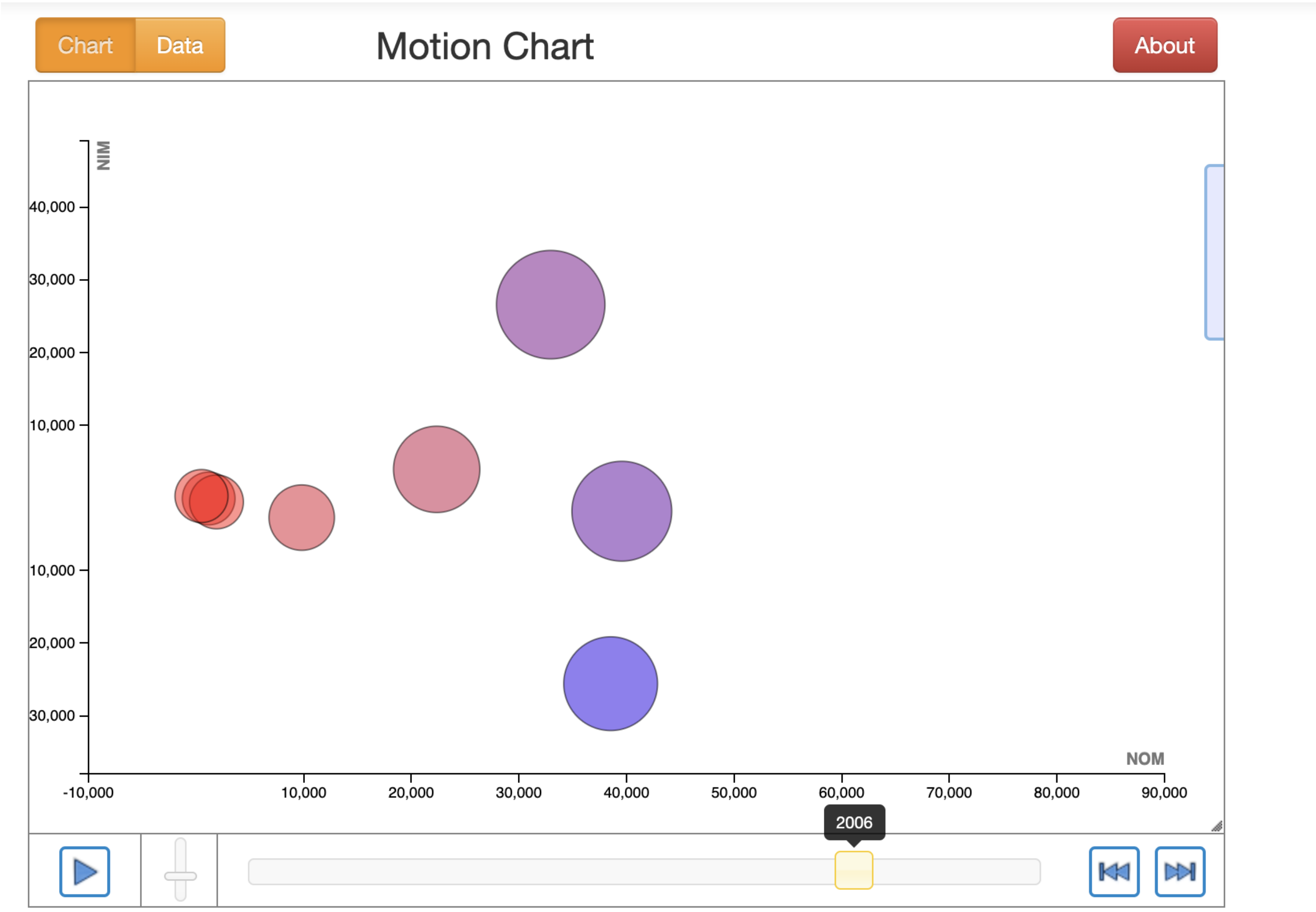
The value of NOM and NIM tends to keep contracting after expansion and then expaning again after severals(e.g. 1983, 1995 and 2003)

In [20]:

```
#A3.2.b
nom.Year[nom.VIC > nom.NSW]
```

Out[20]:

```
29    2006
Name: Year, dtype: int64
```



A3.2.c

In [21]:

```
#A3.2.c
a3.State[a3.NIM.idxmax()]
```

Out[21]:

```
'QLD'
```

Task B

B1

B1.1

In [22]:

```
#1.1
cssa = pd.read_csv('Datasets/Task B/Crime_Statistics_SA_2014_2019.csv')
b11 = cssa.groupby(['Suburb - Incident', 'Reported Date'])['Offence Count'].sum
()
b11 = b11[b11>=15].groupby('Suburb - Incident').count()
b11
```

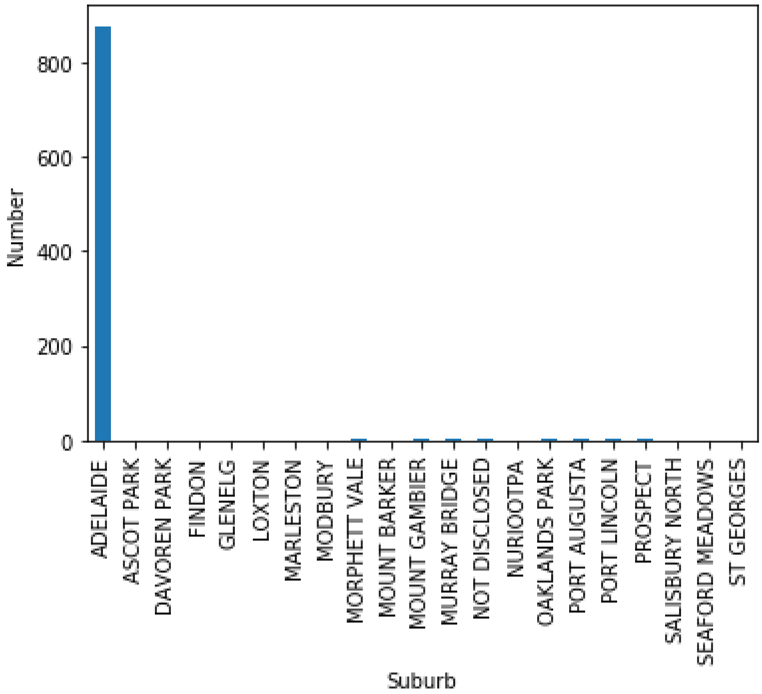
Out[22]:

```
Suburb - Incident
ADELAIDE            877
ASCOT PARK            1
DAVOREN PARK          1
FINDON                1
GLENELG               1
LOXTON                1
MARLESTON             1
MODBURY               1
MORPHETT VALE         3
MOUNT BARKER          1
MOUNT GAMBIER         3
MURRAY BRIDGE         5
NOT DISCLOSED         5
NURIOOTPA             1
OAKLANDS PARK         3
PORT AUGUSTA          4
PORT LINCOLN          5
PROSPECT              2
SALISBURY NORTH       1
SEAFORD MEADOWS       1
ST GEORGES            1
Name: Offence Count, dtype: int64
```

B1.2

In [23]:

```
#1.2
ax = b11.plot.bar(x = 'Suburb - Incident', y = '', rot = 90)
plt.xlabel('Suburb')
plt.ylabel('Number')
plt.show()
```

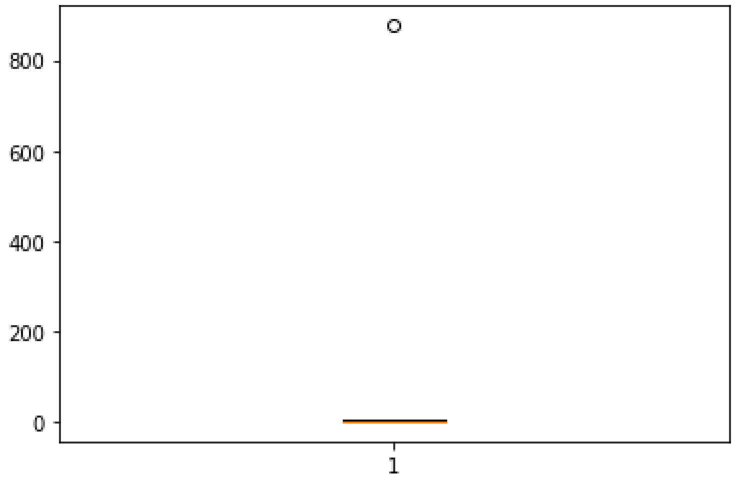


B1.3

In [24]:

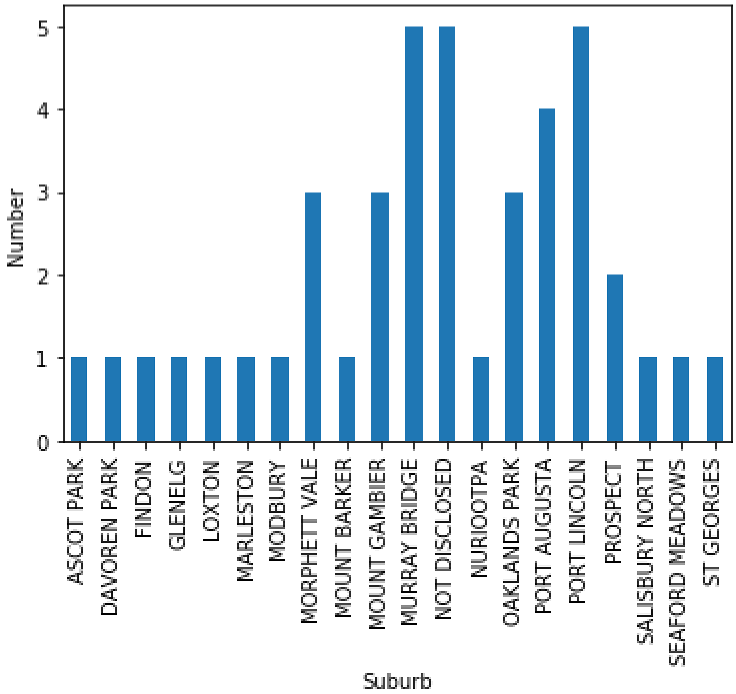
```
#1.3

plt.boxplot(b11)
plt.show()
```



In [25]:

```
b11.drop(index = 'ADELAIDE', inplace = True)
ax = b11.plot.bar(x = 'Suburb - Incident', y = '', rot = 90)
plt.xlabel('Suburb')
plt.ylabel('Number')
plt.show()
```



B1.4

Step 3 is easier to interpret, because the data of ADELAIDE is much higher than other suburbs, so after removing ADELAIDE, it is easier to analyse the differences among other suburbs.

B2.1

In [26]:

```
#2.1
qb2 = cssa.groupby(['Postcode - Incident', 'Reported Date'])['Offence Count'].su
m()
qb2 = qb2[qb2>= 15].groupby('Postcode - Incident').count()
qb2
```

Out[26]:

```
Postcode - Incident
5000            723
5000.0          153
5007.0            1
5015              1
5023              1
5033.0            1
5043.0            1
5045              2
5045.0            1
5046              4
5046.0            1
5061              1
5064.0            1
5082              1
5082.0            1
5085              1
5086              1
5086.0            1
5092              1
5095              1
5108            235
5108.0           33
5112            143
5112.0           30
5113             38
5113.0            5
5114             25
5114.0            2
5158              1
5162              6
5162.0            3
5163              1
5163.0            1
5169              2
5251              1
5253              7
5253.0            2
5290              3
5333              1
5355              1
5540              1
5606              3
5606.0            2
5608              9
5608.0            2
5700              8
5700.0            2
NOT DISCLOSED     5
Name: Offence Count, dtype: int64
```

B2.2

The postcode contains float data that contains '.0', these data would lead to incorrect counts on postcode. For example, 5000 and 5000.0 are the same code, however they would not be identified as same. Also, there are data named 'NOT DISCLOSED'.

Solution: replace the 'NOT DISCLOSED' with int 0 and convert the float number to int

In [27]:

```
#b2.2

#cssa['Postcode - Incident'] = cssa[cssa['Postcode - Incident'] != 'NOT DISCLOSE
D']
cssa['Postcode - Incident'].replace('NOT DISCLOSED', '0', inplace = True)
#cssa['Postcode - Incident'].dropna()
cssa['Postcode - Incident'].fillna('0', inplace = True)
cssa['Postcode - Incident'] = cssa['Postcode - Incident'].astype('float').astype
('int')


qb22 = cssa.groupby(['Postcode - Incident', 'Reported Date'])['Offence Count'].s
um()
qb22 = qb22[qb22>= 15].groupby('Postcode - Incident').count()
qb22
```

Out[27]:

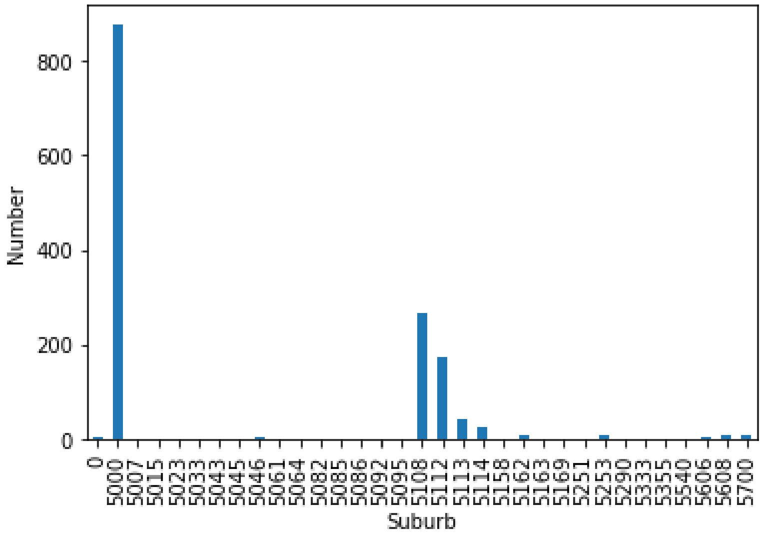
```
Postcode - Incident
0          6
5000     876
5007       1
5015       1
5023       1
5033       1
5043       1
5045       3
5046       5
5061       1
5064       1
5082       2
5085       1
5086       2
5092       1
5095       1
5108     268
5112     173
5113      43
5114      27
5158       1
5162       9
5163       2
5169       2
5251       1
5253       9
5290       3
5333       1
5355       1
5540       1
5606       5
5608      11
5700      10
Name: Offence Count, dtype: int64
```

B2.3

In [28]:

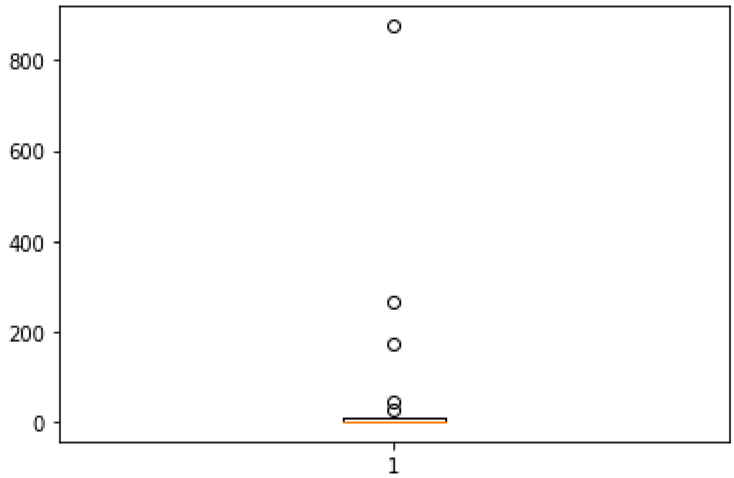
```
#B2.3

ax = qb22.plot.bar(x = 'Postcode - Incident', y = '', rot = 90)
plt.xlabel('Suburb')
plt.ylabel('Number')
plt.show()
```



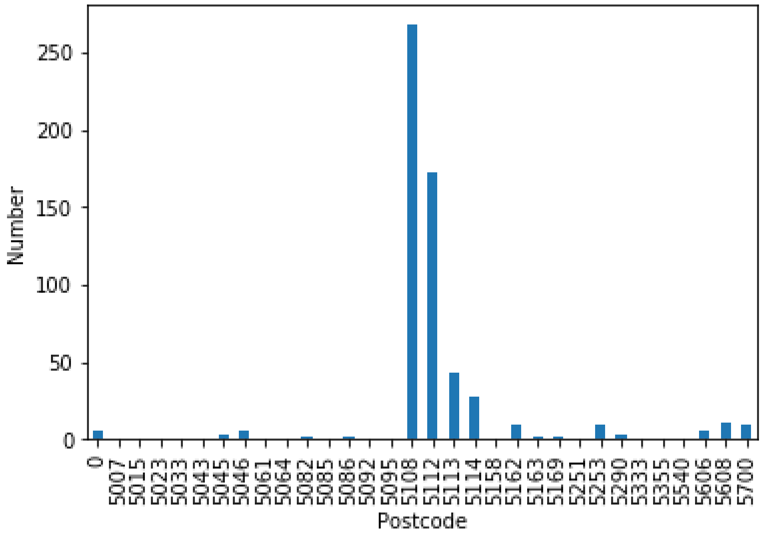
In [29]:

```
plt.boxplot(qb22)
plt.show()
```



In [30]:

```
qb22.drop(index = 5000, inplace = True)
ax = qb22.plot.bar(x = 'Postcode - Incident', y = '', rot = 90)
plt.xlabel('Postcode')
plt.ylabel('Number')
plt.show()
```



After fixing the errors, there are more data that greater than 10 in B3 compared with B1, and besides of the suburb with postcode of 5000, the suburbs with postcode of 5108 and 5112 are also obviously greater than other data, so the graph containing 5000 may better show the trend.

Task C

In this task I find a dataset named 'Suicide Rates Overview 1985 to 2016' from https://www.kaggle.com/russellyates88/suicide-rates-overview-1985-to-2016/downloads/suicide-rates-overview-1985-to-2016.zip/1 (https://www.kaggle.com/russellyates88/suicide-rates-overview-1985-to-2016/downloads/suicide-rates-overview-1985-to-2016.zip/1)

In [31]:

```
sro = pd.read_csv('master.csv')
sro.head()
```

Out[31]:

	country	year	sex	age	suicides_no	population	suicides/100k pop	country-year	HDI for year	gd
0	Albania	1987	male	15-24 years	21	312900	6.71	Albania1987	NaN	2,1
1	Albania	1987	male	35-54 years	16	308000	5.19	Albania1987	NaN	2,1
2	Albania	1987	female	15-24 years	14	289700	4.83	Albania1987	NaN	2,1
3	Albania	1987	male	75+ years	1	21800	4.59	Albania1987	NaN	2,1
4	Albania	1987	male	25-34 years	9	274300	3.28	Albania1987	NaN	2,1

In [32]:

```
condition1 = sro['country']=='Albania'
condition2 = sro['sex']=='male'
condition3 = sro['sex']=='female'
func1 = {'suicides_no':{'male': 'sum'}}
func2 = {'suicides_no':{'female': 'sum'}}
q1 = sro[condition1 & condition2]
q1a = q1.groupby(['year','sex']).agg(func1)
q1b = sro[condition1 & condition3]
q1b = q1b.groupby(['year','sex']).agg(func2)
q11 = pd.merge(q1a, q1b, on=['year'])
q11 = q11.reset_index()
q11.columns = q11.columns.droplevel(0)
q11.rename(columns = {'':'year'}, inplace = True)
q11
```

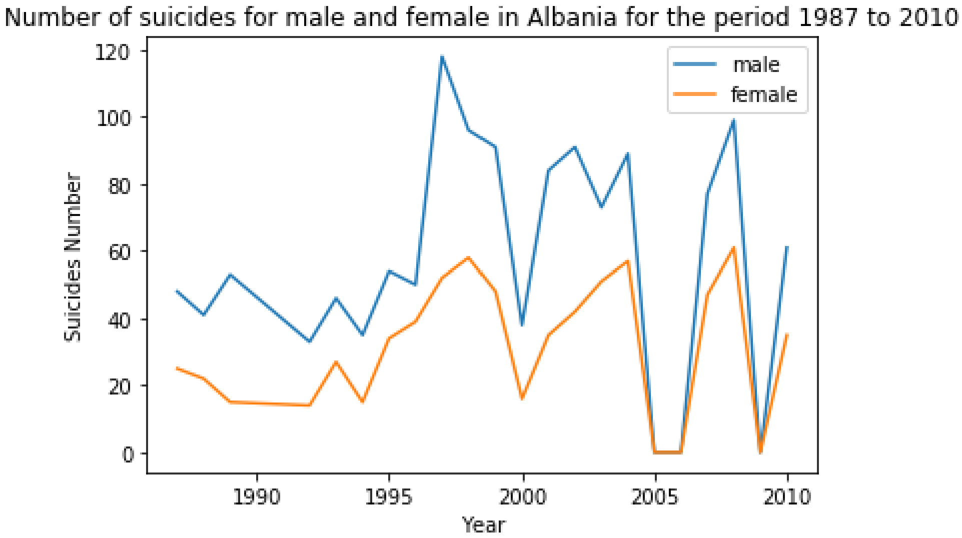
```
/Users/linch/anaconda3/lib/python3.7/site-packages/pandas/core/group
by/generic.py:1315: FutureWarning: using a dict with renaming is dep
recated and will be removed in a future version
  return super(DataFrameGroupBy, self).aggregate(arg, *args, **kwarg
s)
```

Out[32]:

	year	male	female
0	1987	48	25
1	1988	41	22
2	1989	53	15
3	1992	33	14
4	1993	46	27
5	1994	35	15
6	1995	54	34
7	1996	50	39
8	1997	118	52
9	1998	96	58
10	1999	91	48
11	2000	38	16
12	2001	84	35
13	2002	91	42
14	2003	73	51
15	2004	89	57
16	2005	0	0
17	2006	0	0
18	2007	77	47
19	2008	99	61
20	2009	0	0
21	2010	61	35

In [33]:

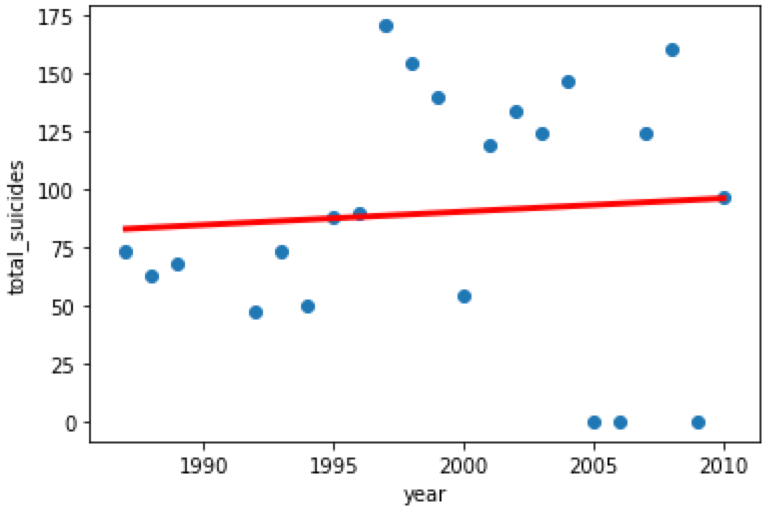
```
plt.plot(q11.year, q11.male, q11.year, q11.female)
plt.xlabel('Year')
plt.ylabel('Suicides Number')
plt.title('Number of suicides for male and female in Albania for the period 1987 to 2010')
plt.legend(['male','female'], loc='best')
plt.show()
```



In [34]:

```
q2 = sro[condition1]
func = {'suicides_no': {'total_suicides': 'sum'}}
q2 = q2.groupby('year').agg(func)
q2 = q2.reset_index()
q2.columns = q2.columns.droplevel(0)
q2.rename(columns = {'':'year'}, inplace = True)

slope, intercept, r_value, p_value, std_err = linregress(q2['year'],q2['total_su
icides'])
line = [slope*xi + intercept for xi in q2['year']]
plt.xlabel('year')
plt.ylabel('total_suicides')
plt.plot(q2['year'], line, 'r-', linewidth = 3)
plt.scatter(q2['year'], q2['total_suicides'])
plt.show()
```



The graph above shows that the total suicides in Albania are increasing slightly from 1987 to 2010.

In [35]:

```
suicide2020 = int(slope * 2020 + intercept)
print("The predicition of suicides in 2020 for Albania is", suicide2020)
```

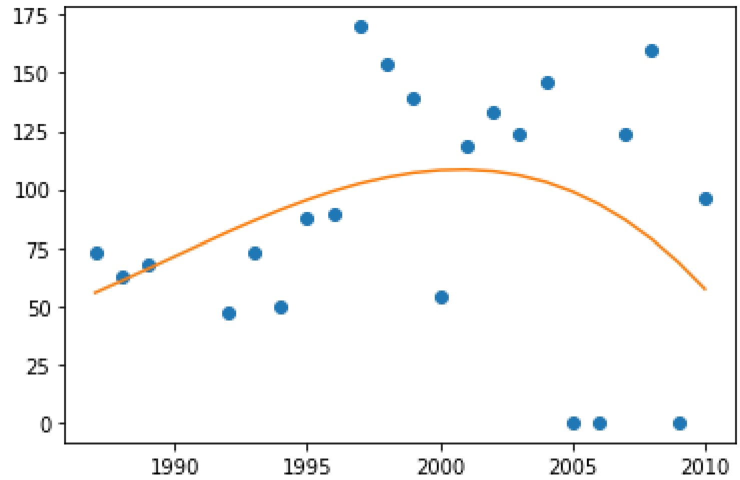
```
The predicition of suicides in 2020 for Albania is 101
```

In [36]:

```
coef = np.polyfit(q2.year, q2.total_suicides, 3)
line = np.poly1d(coef)

plt.figure()
plt.plot(q2.year, q2.total_suicides, 'o', q2.year, line(q2.year))
plt.show()

suicide2020 = int(line(2020))
print(suicide2020)
```




```
-165
```

In this case, the polyfit figure leads to a negative value, obviously it is an impossible number for suicides, so the predicition of suicides in 2020 for Albania is 101