A1.1

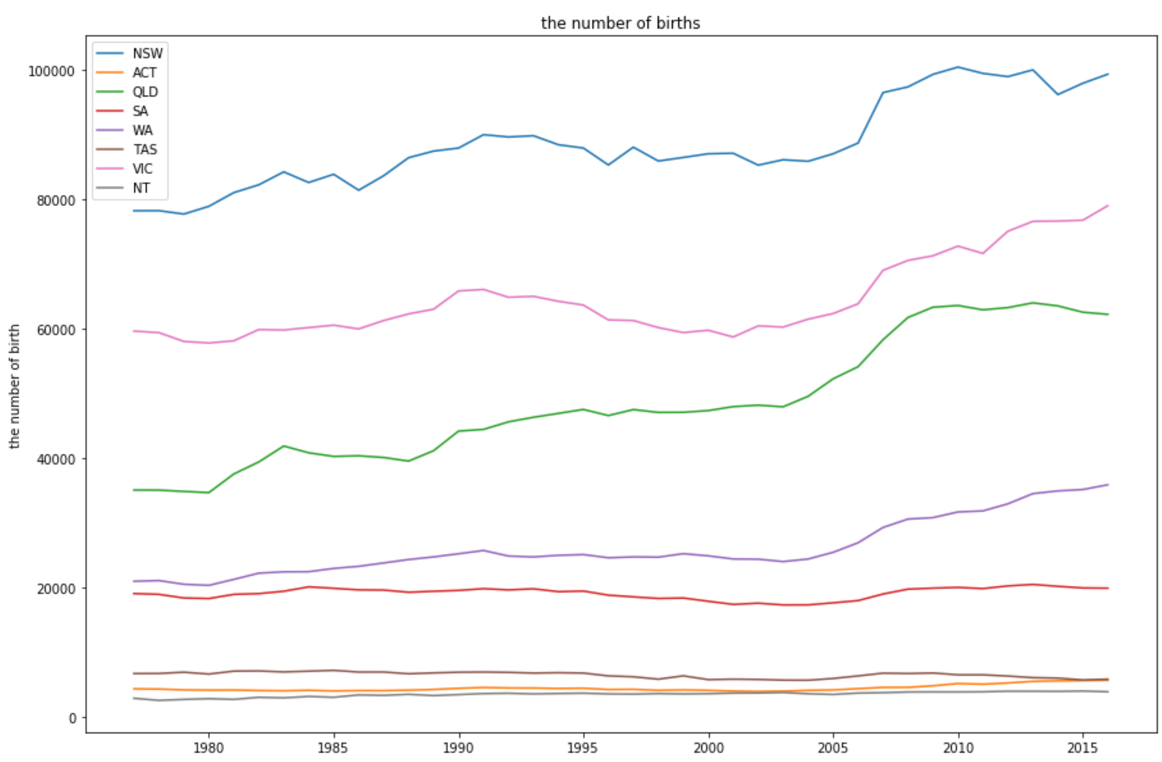
Using Python, plot the number of births recorded in each state/territory for different Australian states over different years.

a

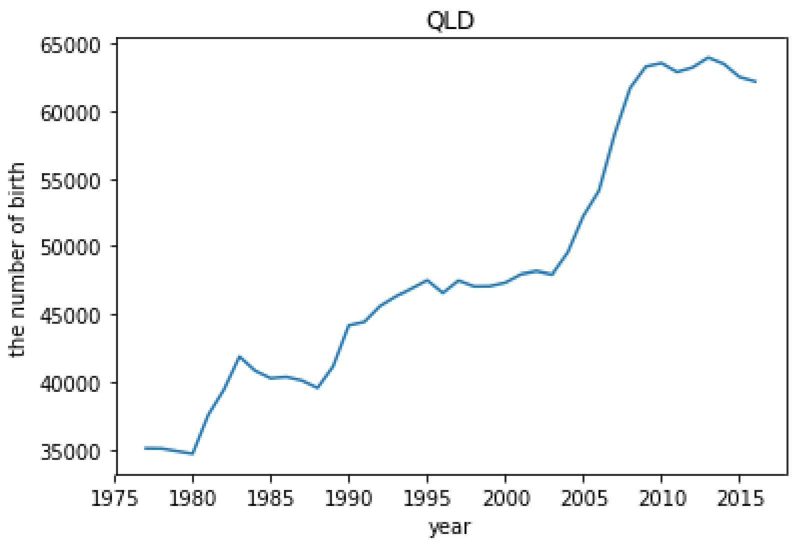
Describe the trend in number of births for Queensland and Tasmania for the period 1977 to 2016?

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:
```
birth_df = pd.read_csv('births.csv', index_col=0) #read csv file
plt.figure(figsize = (15, 10))
plt.plot(birth_df)
plt.legend(birth_df.columns.values)
plt.title('the number of births')
plt.xlabel('year')
plt.ylabel('the number of birth')
plt.show()
```

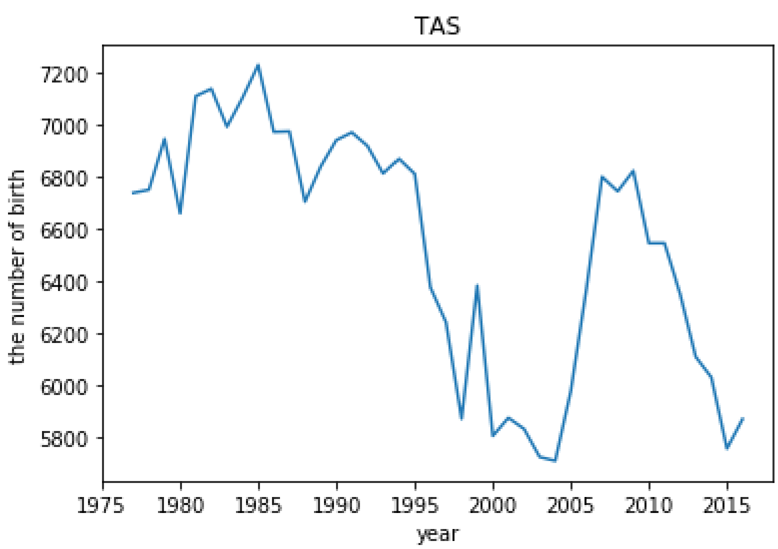


In [3]:
```
plt.plot(birth_df['QLD'])
plt.title('QLD')
plt.xlabel('year')
plt.ylabel('the number of birth')
plt.show()
```



The trend has generally increased

In [4]:
```
plt.plot(birth_df['TAS'])
plt.title('TAS')
plt.xlabel('year')
plt.ylabel('the number of birth')
plt.show()
```

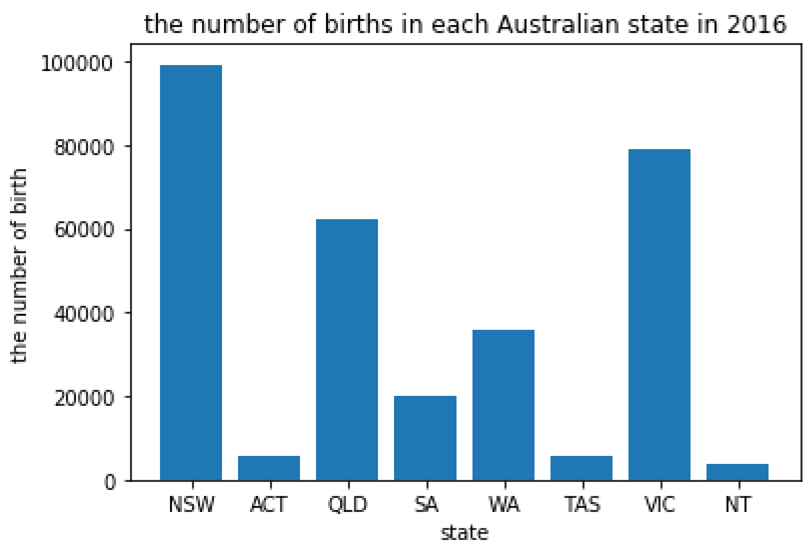


The trend generally fluctuating decrease. During 1975-1985, the number of birth has increased, after 1985 the number of birth decrease. Between 1997 and 2000, there was a sharp fluctuation in the number of births. After 2005, the number of birth has increased to approximate 6800, After that, the number of births has dropped sharply.

b

Draw a bar chart to show the number of births in each Australian state in 2016.

In [5]:
```
plt.bar(birth_df.columns.values, birth_df.loc[2016])
plt.xlabel('state')
plt.ylabel('the number of birth')
plt.title('the number of births in each Australian state in 2016')
plt.show()
```



A1.2

We will now investigate the trend in the total number of births over different years. For this, you will need to aggregate the total number of births registered in Australia by year.

In [6]:
```
total_birth = pd.DataFrame(birth_df.apply(lambda x: x.sum(), axis = 1))
total_birth.rename(columns = {0: 'total_birth'}, inplace = True)
total_birth
```

Year	
1977	226954
1978	226359
1979	223370
1980	223664
1981	230920
1982	237076
1983	241764
1984	240544
1985	241814
1986	239115
1987	242797
1988	246200
1989	250155
1990	257521
1991	261158
1992	259653
1993	260494
1994	258819
1995	258561
1996	250842
1997	254146
1998	249749
1999	250687
2000	250424
2001	249175
2002	249339
2003	249107
2004	252024
2005	258321
2006	265991
2007	287178
2008	295137

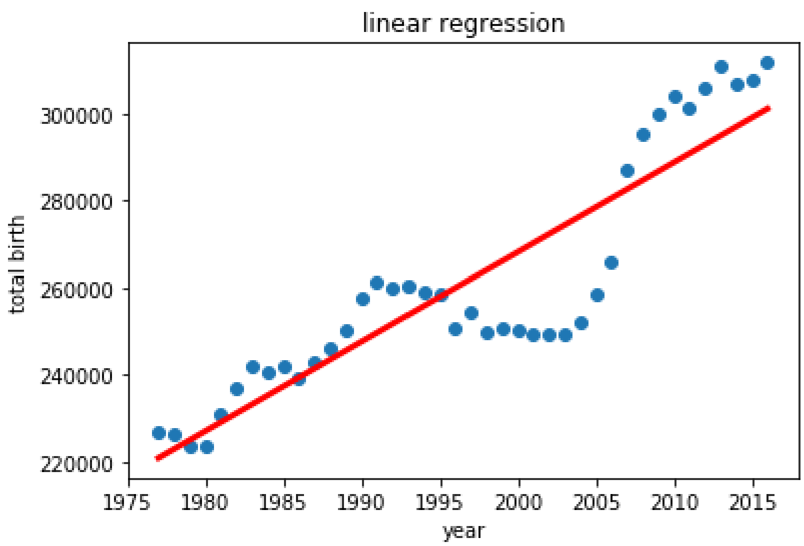
Year	total_birth
2009	300055
2010	303995
2011	301133
2012	305987

a

Fit a linear regression using Python to the above aggregated data (i.e., total number of births registered in Australia over time) and plot the linear fit.

In [7]:

```
from scipy.stats import linregress
slope, intercept, r_value, p_value, std_err = linregress(total_birth.index.va
line = [slope*xi + intercept for xi in total_birth.index]
plt.scatter(total_birth.index, total_birth.loc[:,'total_birth'])
plt.plot(total_birth.index, line, 'r-', linewidth=3)
plt.xlabel('year')
plt.ylabel('total birth')
plt.title('linear regression')
plt.show()
```



b

Does it look like a good fit to you? Identify the period time having any unusual trend(s) in your plot.

No. During 1983 to 2015, the total birth fluctuated increase. but the liner regression is Straight up.

c

Use the linear fit to predict the total births in Australia for the years 2050 and 2100.

In [8]:

```
total_birth_2050 = slope * 2050 + intercept
print('the total births in Australia for the years 2050 is:' + str(total_birt
total_birth_2100 = slope * 2100 + intercept
print('the total births in Australia for the years 2100 is:' + str(total_birt
```

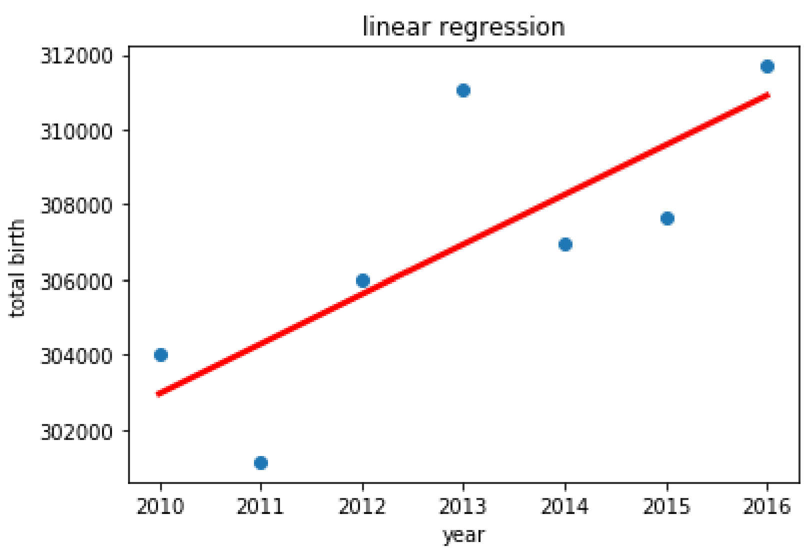
```
the total births in Australia for the years 2050 is:370945.74399624765
the total births in Australia for the years 2100 is:473754.2430581609
```

d

Instead of fitting the linear regression to all of the data, try fitting it to just the most recent data points (say from 2010 onwards). How is the fit? Which model would give better predictions of future population of Australia do you think and why?

In [9]:

```
total_part = total_birth.loc['2010':]
slope, intercept, r_value, p_value, std_err = linregress(total_part.index.val
line = [slope*xi + intercept for xi in total_part.index.values]
plt.scatter(total_part.index.values, total_part['total_birth'])
plt.plot(total_part.index.values, line, 'r-', linewidth=3)
plt.xlabel('year')
plt.ylabel('total birth')
plt.title('linear regression')
plt.show()
```



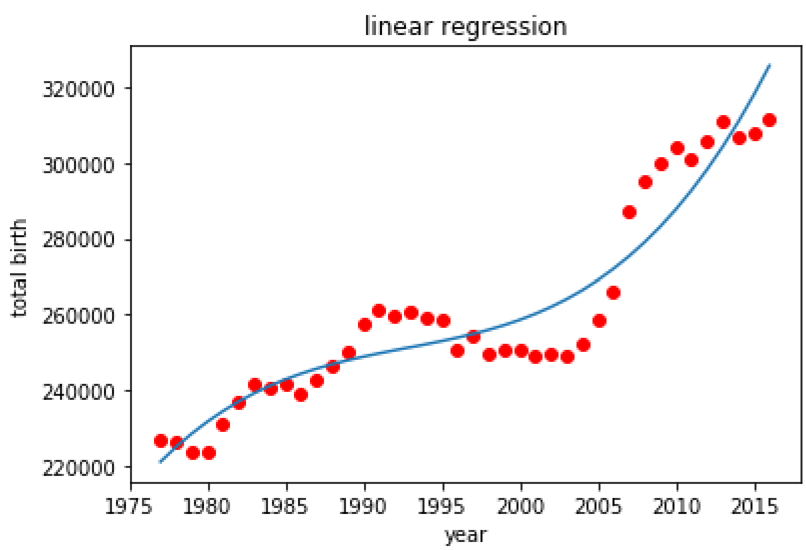
This is better than the last model. I will chose this model to predict the future population of Australia, because this linear regression is more relevant to these point.

e: challenge

Can you think of a better model than linear regression to fit to all of the data to capture the trend in the number of births.

In [10]:
```
total_birth.reset_index(drop=False, inplace=True)
```

In [11]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
poly_reg = PolynomialFeatures(degree=4)
X_poly = poly_reg.fit_transform(total_birth.loc[:,'Year'].values.reshape(-1,1
pol_reg = LinearRegression()
pol_reg.fit(X_poly, total_birth.loc[:,'total_birth'])
plt.scatter(total_birth.loc[:, 'Year'], total_birth.loc[:,'total_birth'], col
plt.plot(total_birth.loc[:, 'Year'], pol_reg.predict(poly_reg.fit_transform(t
plt.xlabel('year')
plt.ylabel('total birth')
plt.title('linear regression')
plt.show()
```



In [12]:
```
print('the total births of Australia at 2050 is:'+str(pol_reg.predict(poly_re
print('the total births of Australia at 2100 is:'+str(pol_reg.predict(poly_re
```

```
the total births of Australia at 2050 is:1148774.1656742096
the total births of Australia at 2100 is:6049884.466032028
```

reference

Machine Learning: Polynomial Regression with Python. Nhan Tan. Retrieved from https://towardsdatascience.com/machine-learning-polynomial-regression-with-python-5328e4e8a386 (https://towardsdatascience.com/machine-learning-polynomial-regression-with-python-5328e4e8a386)

A1.3

Inspect the data on Total Fertility Rate (TFR.csv) for Queensland and Northern Territory.

a

What was the minimum value for TFR recorded in the dataset for Queensland and when did that occur? What was the corresponding TFR value for Northern Territory in the same year?

In [13]:

```
TFR_df = pd.read_csv('TFR.csv')
QLD_min = min(TFR_df['QLD'])
index_1 = TFR_df[TFR_df['QLD']==QLD_min].index.values[0]
print('the minimum values for TFR recorded in the dataset for Queensland is:'
print('the year when it occured is:' + str(TFR_df.iloc[index_1,0]))
print('the TFR in the same year is:' + str(TFR_df.loc[index_1, 'NT']))
```

```
the minimum values for TFR recorded in the dataset for Queensland is:1.8
the year when it occured is:1999
the TFR in the same year is:2.123
```

A1.4

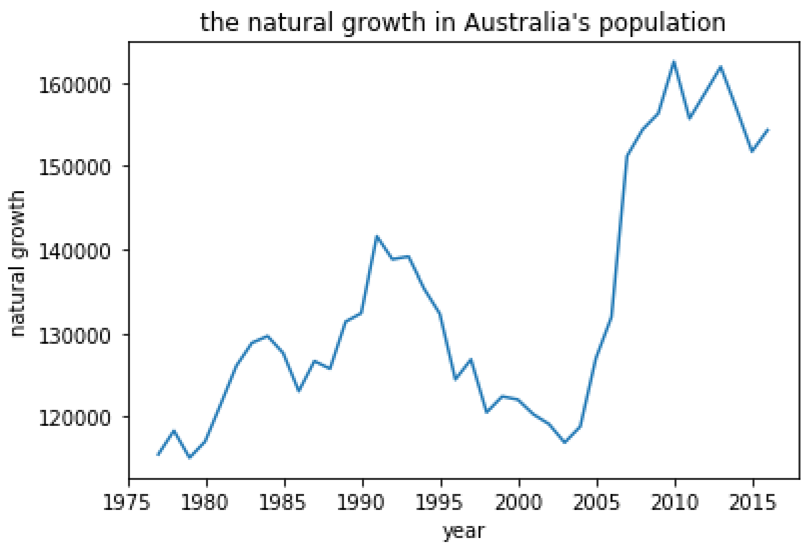
Next, plot the natural growth in Australia's population over different years. For this, you will need to aggregate the total births and deaths by year. (HINT: Natural growth in a population is the difference between the total numbers of births and deaths in a population, for instance, Natural Growth of Australia's Population = Total Births in Australia - Total Deaths in Australia)

In [14]:

```
total_birth = total_birth.set_index('Year')
```

In [15]:

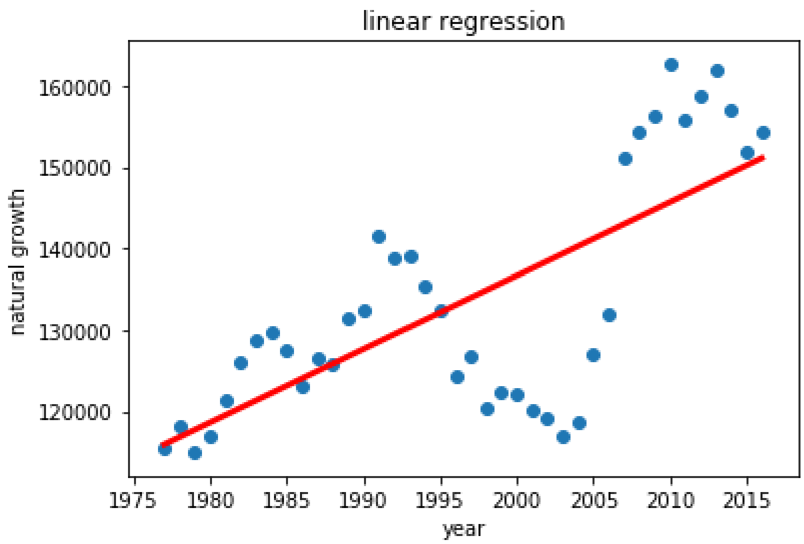
```
death_df = pd.read_csv('Deaths.csv', index_col = 0)
total_death = pd.DataFrame(death_df.apply(lambda x: x.sum(), axis = 1))
total_death.rename(columns = {0: 'total_death'}, inplace = True)
N_A = pd.merge(total_death, total_birth, left_index = True, right_index = Tru
N_A['nature growth'] = N_A.apply(lambda x: x[1] - x[0], axis = 1)
plt.plot(N_A.index.values, N_A['nature growth'])
plt.xlabel('year')
plt.ylabel('natural growth')
plt.title('the natural growth in Australia\'s population')
plt.show()
```



a

Describe the trend in natural growth in Australian population over time using linear regression?

In [16]:
```
slope, intercept, r_value, p_value, std_err = linregress(N_A.index.values, N_
line = [slope*xi + intercept for xi in N_A.index.values]
plt.plot(N_A.index.values, line, 'r-', linewidth = 3)
plt.scatter(N_A.index.values, N_A['nature growth'])
plt.xlabel('year')
plt.ylabel('natural growth')
plt.title('linear regression')
plt.show()
```



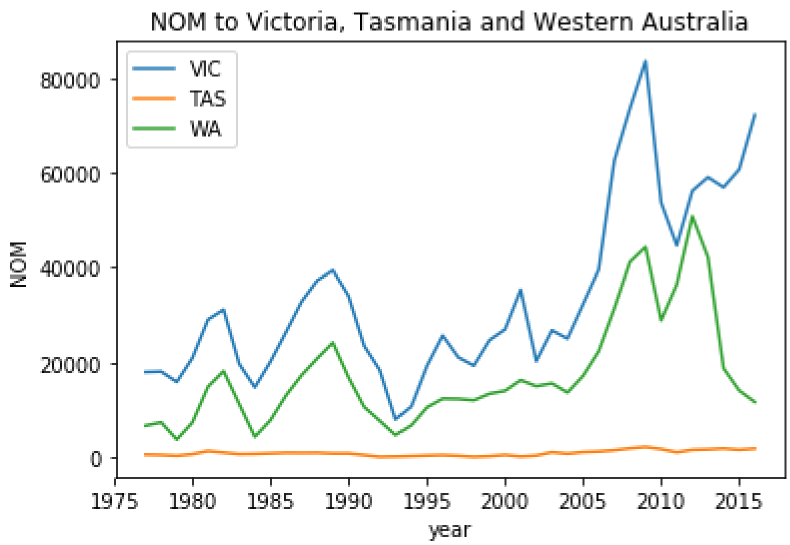
A2.1

Let’s look at the Net Overseas Migration (NOM) data in different states over time.

a

Use Python to plot the NOM to Victoria, Tasmania and Western Australia over time. Explain and compare the trend in all three states (VIC, TAS and WA).

In [17]:
```
NOM_df = pd.read_csv('NOM.csv', index_col = 0)
plt.plot(NOM_df['VIC'], label = 'VIC')
plt.plot(NOM_df['TAS'], label = 'TAS')
plt.plot(NOM_df['WA'], label = 'WA')
plt.legend()
plt.xlabel('year')
plt.ylabel('NOM')
plt.title('NOM to Victoria, Tasmania and Western Australia')
plt.show()
```



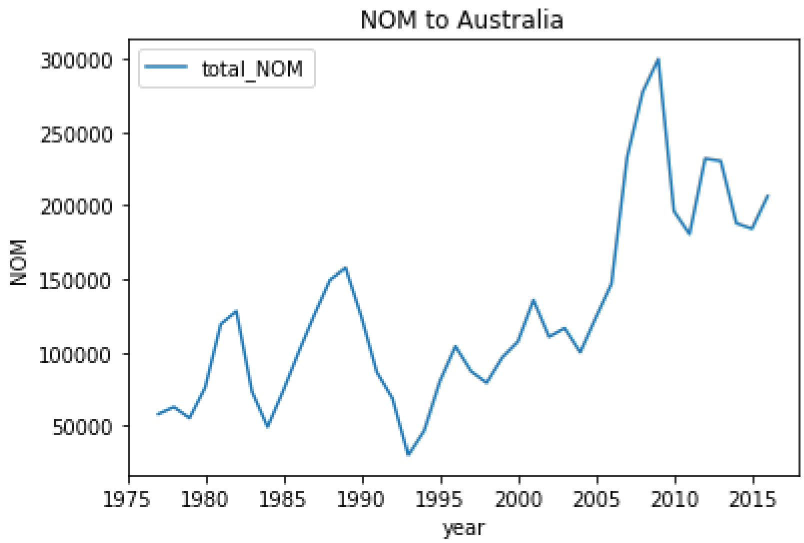
TAS: The trend of TAS is flat and its value has been fluctuating around 0 WA has the same trend as the VIC between 1975 to 2012. WA and VIC both have two fluctuations from 1975 to 1993. During 1975 to 1994, VIC decreased fluctuated, WA has two growths and two declines, and the value in 1994 is about the same as the value in 1975. After 1993, WA and VIC both increased, but the VIC has a sharply increase after 2005. VIC and WA both decreased from 2007 to 2010, after that they both increased until 2012. After 2012, VIC increased, WA decreased.

b

Plot the Net Overseas Migration (NOM) to Australia over time. Do you find the trend strange? Explain the reason to your answer (Hint: You might go online to find contributing factors to this trend).

In [18]:
```
total_NOM = pd.DataFrame(NOM_df.apply(lambda x: x.sum(), axis = 1))
total_NOM.rename(columns = {0: 'total_NOM'}, inplace = True)
total_NOM.plot()
plt.xlabel('year')
plt.ylabel('NOM')
plt.title('NOM to Australia')
```

Out[18]: `Text(0.5, 1.0, 'NOM to Australia')`



In 2005, the Australian government implemented some immigration policies, resulting in a substantial increase in NOM.

A2.2

Now let's look at the relationship between Net Overseas Migration (NOM) and Net Interstate Migration (NIM).

a

Use Python to combine the data from the different files into a single table. The resulting table should contain the NOM and NIM values for each of the states for a given year. What are the first year and last year for the combined data?

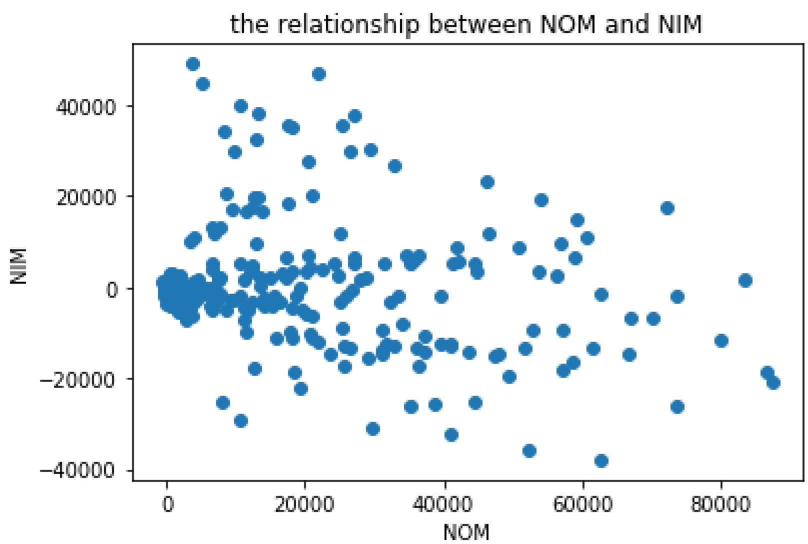
In [19]:
```
NIM_df = pd.read_csv('NIM.csv', index_col = 0)
multi_colum = pd.MultiIndex.from_product([['NOM','NIM'], ['NSW', 'VIC', 'QLD'
NOM_NIM = pd.merge(NOM_df, NIM_df, left_index = True, right_index = True)
NOM_NIM.columns = multi_colum
print('The first year is:'  + str(NOM_NIM.index[0]))
print('The last year is:' + str(NOM_NIM.index[-1]))
```

```
The first year is:1977
The last year is:2016
```

b

Now that you have the data combined, we can see whether there is a relationship between NOM and NIM. Plot the values against each other using scatter plot. Can you see any relationship between NOM and NIM?

In [20]:
```
plt.scatter(NOM_NIM.loc[:,'NOM'],NOM_NIM.loc[:,'NIM'])
plt.xlabel('NOM')
plt.ylabel('NIM')
plt.title('the relationship between NOM and NIM')
plt.show()
```



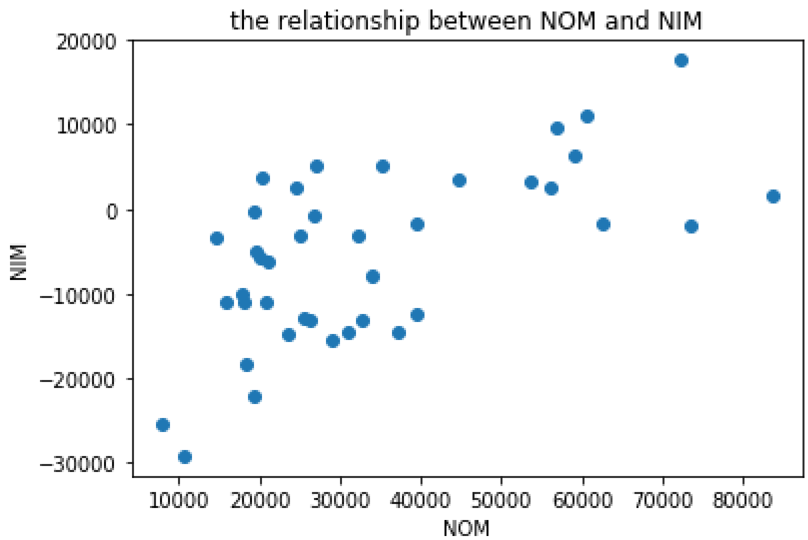
No, I can not see any relationship

c

Try selecting and plotting the data for Victoria only using scatter plot. Can you see a relationship now? If so, explain the relationship.

In [21]:

```
plt.scatter(NOM_NIM.loc[:,('NOM','VIC')], NOM_NIM.loc[:,('NIM','VIC')])
plt.xlabel('NOM')
plt.ylabel('NIM')
plt.title('the relationship between NOM and NIM')
plt.show()
```

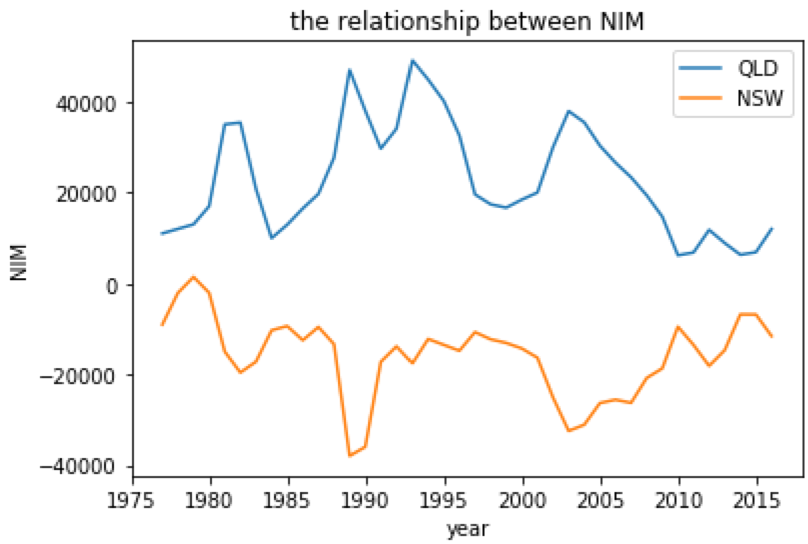


NOM and NIM is Linear relationship

d

Finally, plot the Net Interstate Migration (NIM) for Queensland and New South Wales over different years. Note graphs for both QLD and NSW should be on the same plot. Compare the plots for these two states. What can you infer from the trend you see for these two states?

In [22]:
```
plt.plot(NIM_df.index.values, NIM_df['QLD'], label = 'QLD')
plt.plot(NIM_df.index.values, NIM_df['NSW'], label = 'NSW')
plt.legend()
plt.ylabel('NIM')
plt.xlabel('year')
plt.title('the relationship between NIM')
plt.show()
```



When the QLD increases, the NSW decreases, and when the NSW increases, the QLD decreases.

A3.

Now let's look at the relationship between other variables impacting the population size and growth of Australian states/territories over time. Ensure that you have combined all the data from the different files (Births.csv, Deaths.csv, TFR.csv, NOM.csv and NIM.csv) into a single table.

In [23]:

```
#crete the multicolumn
multi_colum = pd.MultiIndex.from_product([['Births','Deaths','TFR','NOM','NIM
TFR_df.set_index('Year', inplace = True)
birth_df = birth_df[['NSW', 'VIC', 'QLD', 'SA', 'WA', 'TAS', 'NT', 'ACT']]
total_df = pd.concat( [birth_df, death_df, TFR_df, NOM_df, NIM_df], axis=1 )
total_df.columns = multi_colum
total_df
```

1978	78190.0	59364.0	35054.0	18964.0	21094.0	6751.0	2600.0	4342.0	40121.0	2934
1979	77669.0	58006.0	34858.0	18403.0	20523.0	6947.0	2747.0	4217.0	39975.0	2952
1980	78859.0	57768.0	34666.0	18317.0	20354.0	6660.0	2859.0	4181.0	39799.0	2892
1981	80980.0	58104.0	37545.0	18960.0	21277.0	7112.0	2749.0	4193.0	39979.0	2914
1982	82185.0	59842.0	39403.0	19076.0	22236.0	7140.0	3074.0	4120.0	41267.0	2949
1983	84180.0	59768.0	41863.0	19445.0	22442.0	6994.0	2991.0	4081.0	41348.0	3039
1984	82541.0	60143.0	40815.0	20118.0	22463.0	7106.0	3203.0	4155.0	41278.0	2954
1985	83812.0	60515.0	40257.0	19901.0	22967.0	7232.0	3074.0	4056.0	41908.0	3024
1986	81351.0	59935.0	40355.0	19657.0	23290.0	6974.0	3441.0	4112.0	41921.0	3084
1987	83582.0	61231.0	40090.0	19628.0	23811.0	6976.0	3376.0	4103.0	42281.0	3067
1988	86370.0	62256.0	39538.0	19288.0	24339.0	6705.0	3532.0	4172.0	44287.0	3167
1989	87391.0	62985.0	41135.0	19445.0	24745.0	6840.0	3338.0	4276.0	42955.0	3137
1990	87857.0	65799.0	44168.0	19573.0	25231.0	6942.0	3491.0	4460.0	46211.0	3210
1991	89922.0	66031.0	44429.0	19841.0	25736.0	6972.0	3645.0	4582.0	42830.0	3108
1992	89569.0	64823.0	45594.0	19655.0	24880.0	6920.0	3698.0	4514.0	43579.0	3130
1993	89760.0	64965.0	46301.0	19819.0	24741.0	6814.0	3594.0	4500.0	43059.0	3128
1994	88370.0	64205.0	46901.0	19382.0	24990.0	6870.0	3661.0	4440.0	43597.0	3162
1995	87859.0	63619.0	47509.0	19475.0	25104.0	6812.0	3710.0	4473.0	44776.0	3227
1996	85248.0	61327.0	46566.0	18839.0	24614.0	6377.0	3596.0	4275.0	44464.0	3282
1997	87997.0	61233.0	47488.0	18576.0	24744.0	6242.0	3564.0	4302.0	44720.0	3257
1998	85857.0	60145.0	47051.0	18330.0	24706.0	5870.0	3650.0	4140.0	45812.0	3242
1999	86408.0	59375.0	47067.0	18399.0	25244.0	6384.0	3598.0	4212.0	45103.0	3229
2000	86975.0	59734.0	47330.0	17896.0	24910.0	5804.0	3635.0	4140.0	45073.0	3199
2001	87057.0	58689.0	47941.0	17414.0	24429.0	5874.0	3729.0	4042.0	45656.0	3225
2002	85221.0	60407.0	48169.0	17601.0	24391.0	5831.0	3740.0	3979.0	45173.0	3262
2003	86052.0	60220.0	47914.0	17331.0	24025.0	5723.0	3818.0	4024.0	46079.0	3307
2004	85816.0	61442.0	49537.0	17339.0	24419.0	5708.0	3620.0	4143.0	46351.0	3309
2005	86973.0	62310.0	52233.0	17655.0	25453.0	5978.0	3514.0	4205.0	45593.0	3240

Year	Births NSW	VIC	QLD	SA	WA	TAS	NT	ACT	Deaths NSW	VIC
2005	86973.0	62310.0	52233.0	17655.0	25453.0	5978.0	3514.0	4205.0	45593.0	3240
2006	88630.0	63816.0	54106.0	18000.0	26930.0	6372.0	3726.0	4411.0	46105.0	3310
2007	96420.0	68987.0	58275.0	19015.0	29291.0	6801.0	3786.0	4603.0	46206.0	3419
~~**2008**~~	~~97303.0~~	~~70515.0~~	~~61710.0~~	~~19773.0~~	~~30588.0~~	~~6745.0~~	~~3895.0~~	~~4608.0~~	~~47667.0~~	~~3519~~
2009	99233.0	71227.0	63288.0	19923.0	30806.0	6824.0	3905.0	4849.0	48695.0	3603
2010	100355.0	72722.0	63553.0	20033.0	31689.0	6545.0	3901.0	5197.0	47319.0	3505
2011	99385.0	71593.0	62888.0	19856.0	31846.0	6545.0	3922.0	5098.0	49387.0	3642

1

Use Python to build a Motion Chart, that compares the role migration (overseas and interstate) plays towards population growth in each Australia state/territory over time. The motion chart should show the Net Overseas Migration (NOM) on the x-axis, the Net Interstate Migration (NIM) on the y-axis, and the bubble size should show the Total Population Growth.

In [24]:

```
from motionchart.motionchart import MotionChart
TPG_df = birth_df - death_df + NIM_df + NOM_df
TPG_df.reset_index(drop=False, inplace=True)
TPG_df = pd.melt(TPG_df, id_vars=['Year'], var_name = 'region', value_name =
NIM_df.reset_index(drop=False, inplace=True)
NIM = pd.melt(NIM_df, id_vars=['Year'], var_name = 'region', value_name = 'NI
NOM_df.reset_index(drop=False, inplace=True)
NOM = pd.melt(NOM_df, id_vars = ['Year'], var_name = 'region', value_name = '
```

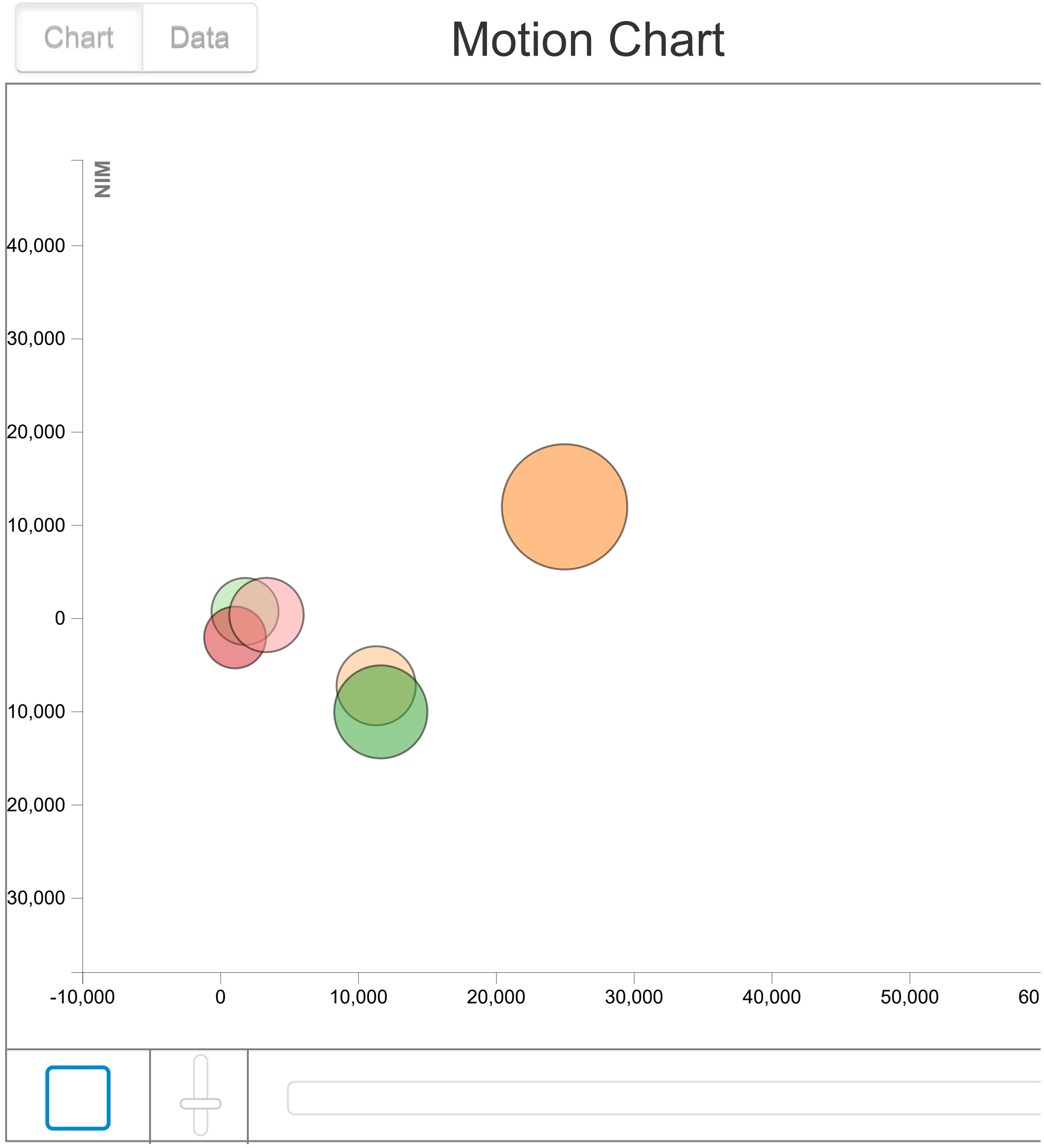
In [25]:

```
A3_df_1 = pd.merge(NIM,NOM,on=('Year','region'))
A3_df = pd.merge(A3_df_1, TPG_df, on=('Year', 'region'))
```

In [26]:

```
%%html
<style>
.output_wrapper, .output {
    height:auto !important;
    max-height:1000px;  /* your desired max-height here */
}
.output_scroll {
    box-shadow:none !important;
    webkit-box-shadow:none !important;
}
</style>
```

In [27]:
```
mChart = MotionChart(df = A3_df, key='Year', x='NOM', y='NIM', xscale='linear
                          size='total population grouth', color='region', category
mChart.to_notebook()
```



2

Run the visualisation from start to end. (Hint: In Python, to speed up the animation, set timer bar next to the play/pause button to the minimum value.) And then answer the following questions:

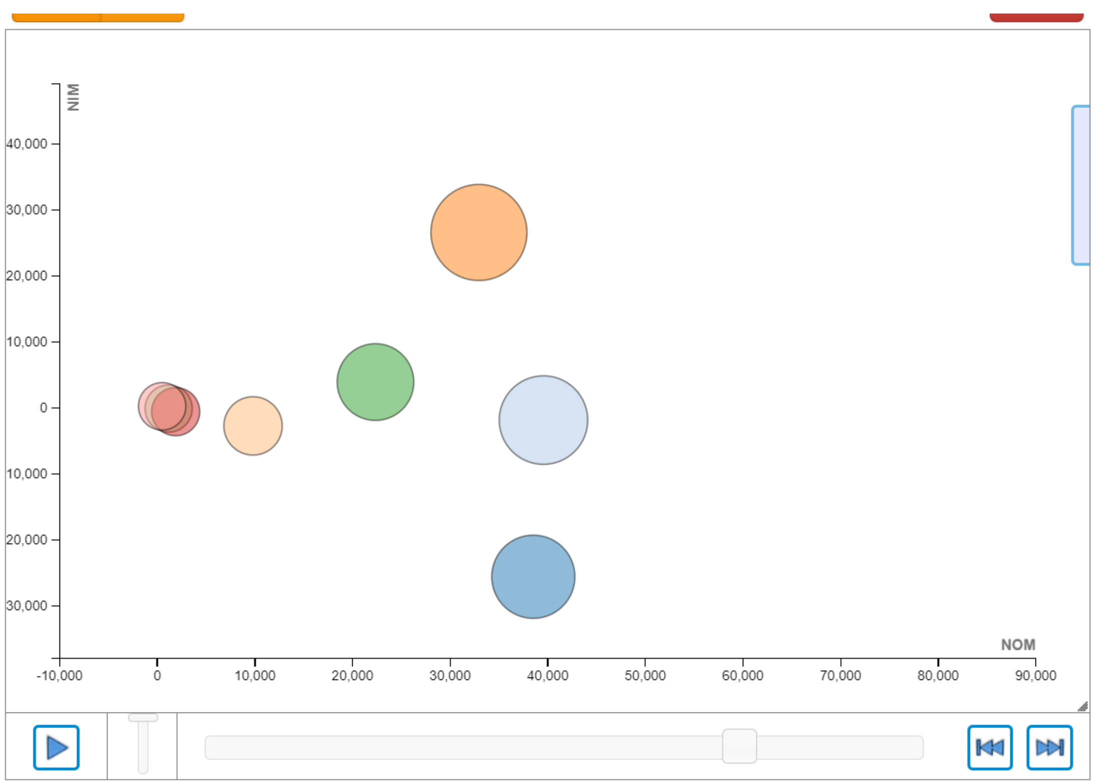
a

Comment generally on the trend you see in Net Overseas Migration (NOM) and Net Interstate Migration (NIM) overtime. Is there any relationship between the two variables?

Yes, they have. The relationship is liner relationship

b

Select VIC and NSW for this question: In which year(s) does VIC have a higher Net Overseas Migration (NOM) than NSW. Please support your answer with a relevant python code and motion chart screenshot.



In [28]:
```
#NOM_df.set_index('Year', inplace = True)
VIC_NOM = NOM_df['VIC']
NSW_NOM = NOM_df['NSW']
VIC_NSW = pd.concat([VIC_NOM, NSW_NOM], axis = 1)
result = VIC_NSW[VIC_NSW["VIC"] > VIC_NSW["NSW"]]
result
```

Out[28]:

	VIC	NSW
29	39561	38523

c

Which state has the highest Net Interstate Migration most of the years (for the period 1977 to 2016)?

QLD has the highest Net Interstate Migration

task B

B1

1

For each suburb, calculate the number of days that at least 15 crimes have occurred per day.

In [29]:
```
crime = pd.read_csv('Crime_Statistics_SA_2014_2019.csv')
```

In [30]:

```
#count the number of offence count
date_crime = crime.groupby(['Suburb - Incident', 'Reported Date']).sum()
date_crime_filter = date_crime[date_crime['Offence Count']>15]
date_crime_filter.groupby('Suburb - Incident').count()
```

Out[30]:

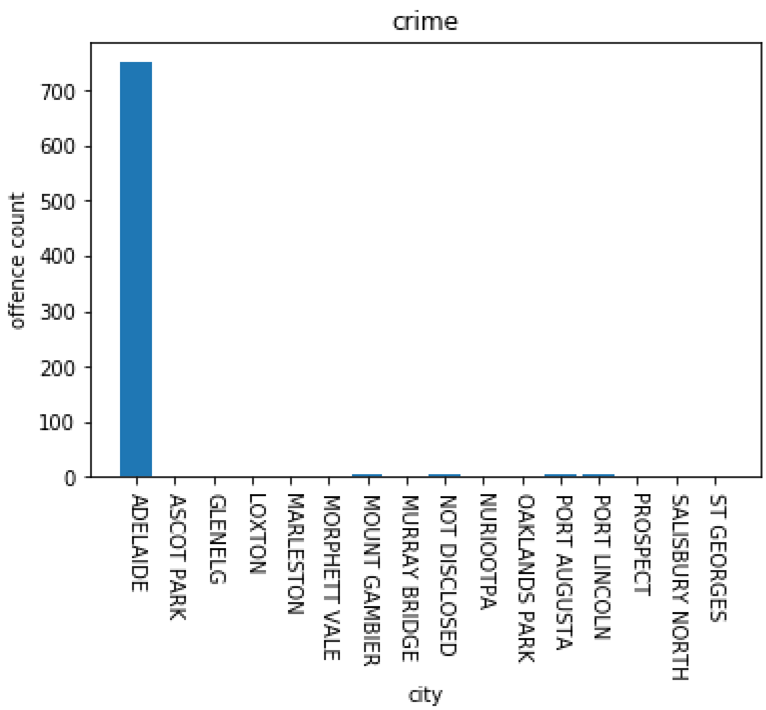
Suburb - Incident	Offence Count
ADELAIDE	752
ASCOT PARK	1
GLENELG	1
LOXTON	1
MARLESTON	1
MORPHETT VALE	2
MOUNT GAMBIER	3
MURRAY BRIDGE	1
NOT DISCLOSED	4
NURIOOTPA	1
OAKLANDS PARK	2
PORT AUGUSTA	3
PORT LINCOLN	4
PROSPECT	1
SALISBURY NORTH	1
ST GEORGES	1

2

Now which suburbs do have at least one day where the daily number of crimes are more than 15. Plot the number of days that at least 15 crimes have occurred for the suburbs you found in this step (step 2) using a bar graph.

In [31]:

```
#group by Suburb - Incident and count the number
date_crime_sub = date_crime_filter.groupby('Suburb - Incident').count()
plt.bar(date_crime_sub.index.values, date_crime_sub['Offence Count'])
plt.xticks(rotation=270)
plt.ylabel('offence count')
plt.xlabel('city')
plt.title('crime')
plt.show()
```

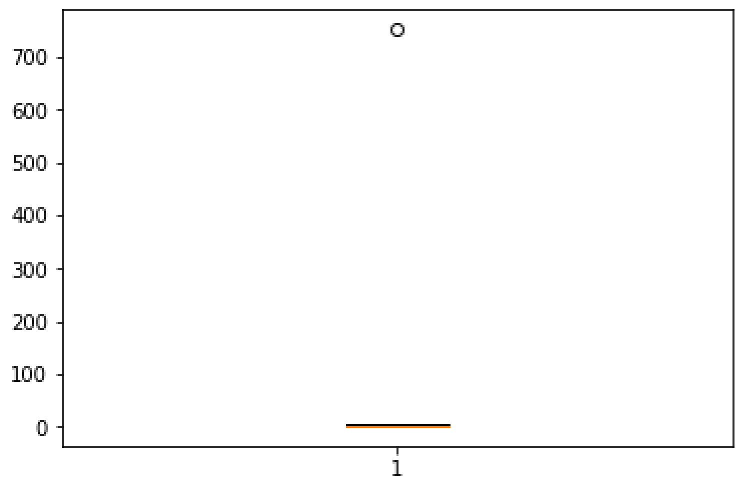


3

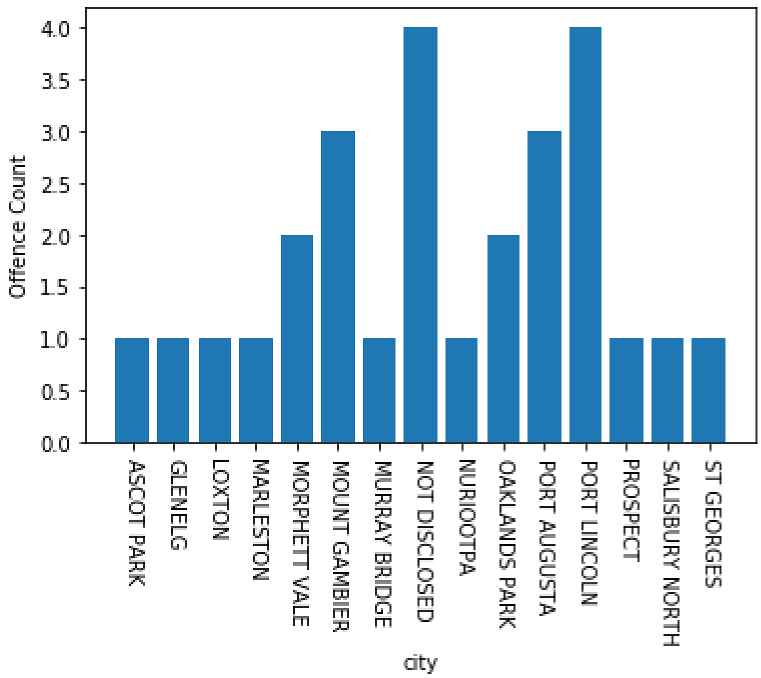
Use an appropriate graph to visualize and detect outliers (extreme values) on the data from step 2 and remove them. Then, plot the data again using a bar graph.

In [32]:
```
plt.boxplot(date_crime_sub['Offence Count'])
```

Out[32]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x219833d26a0>,
  <matplotlib.lines.Line2D at 0x219833d29e8>],
 'caps': [<matplotlib.lines.Line2D at 0x219833d2d30>,
  <matplotlib.lines.Line2D at 0x219833d2e10>],
 'boxes': [<matplotlib.lines.Line2D at 0x219833d2278>],
 'medians': [<matplotlib.lines.Line2D at 0x219833dc400>],
 'fliers': [<matplotlib.lines.Line2D at 0x219833dc748>],
 'means': []}
```



In [33]:
```
plt.bar(date_crime_sub.index[1:], date_crime_sub.iloc[1:, 0])
plt.xticks(rotation=270)
plt.ylabel('Offence Count')
plt.xlabel('city')
plt.show()
```



4

Compare the bar graphs in step 2 and 3. Which bar graph is easier to interpret? Why?

answer: The secand one. Adeladie has large number of offence, we can not see other city's offence count clearly.

B2:challenge: identify mistakes in data entry

```
The mistake data is the Reported Date. Date and month are reversed for each
month from the first day to the twelfth day of each month
```

In [43]:

```
#transfer the format of Reported Date to date format and extract the year, mo
crime = pd.read_csv('Crime_Statistics_SA_2014_2019.csv')
crime.loc[:, 'Reported Date'] = pd.to_datetime(crime.loc[:,'Reported Date'])
crime['month'] = crime.loc[:,'Reported Date'].dt.month
crime['day'] = crime.loc[:,'Reported Date'].dt.day
crime['year'] = crime.loc[:,'Reported Date'].dt.year
#select the wrong date
crime_wrong_date = crime[crime.loc[:,'day']<13]
#change the date
crime_wrong_date['Date'] = crime_wrong_date.loc[:,'year'].map(str)+'-'+crime_
correct_list = crime_wrong_date.loc[:,'Date'].tolist()
crime_wrong_date.loc[:,'Reported Date'] = correct_list
#select the correct date
crime_correct_date = crime[crime.loc[:,'day']>12]
#chang Report date
crime_correct_date['Date'] = crime_correct_date.loc[:, 'year'].map(str)+'-'+c
correct_list_1 = crime_correct_date.loc[:,'Date'].tolist()
crime_correct_date.loc[:,'Reported Date'] = correct_list_1
#link the two dataframe.
correct_date = pd.concat([crime_wrong_date, crime_correct_date], axis=0)
correct_date
```

```
C:\Users\Cyrus\Anaconda3\lib\site-packages\ipykernel_launcher.py:10: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-do
cs/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.
org/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
  # Remove the CWD from sys.path while we load stuff.
C:\Users\Cyrus\Anaconda3\lib\site-packages\ipykernel_launcher.py:16: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-do
cs/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.
org/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
  app.launch_new_instance()
```

Out[43]:

	Reported Date	Suburb - Incident	Postcode - Incident	Offence Level 1 Description	Offence Level 2 Description	Offenc Level Descriptio
0	2014-1-1	ADELAIDE	5000	OFFENCES AGAINST PROPERTY	PROPERTY DAMAGE AND ENVIRONMENTAL	Othe propert damage an environmenta
1	2014-1-1	ADELAIDE	5000	OFFENCES AGAINST PROPERTY	THEFT AND RELATED OFFENCES	Other the
2	2014-1-1	ADELAIDE	5000	OFFENCES AGAINST THE PERSON	ACTS INTENDED TO CAUSE INJURY	Assault Polic
3	2014-1-1	ADELAIDE	5000	OFFENCES AGAINST THE PERSON	ACTS INTENDED TO CAUSE INJURY	Commo Assau
4	2014-1-1	ADELAIDE	5000	OFFENCES AGAINST THE PERSON	ACTS INTENDED TO CAUSE INJURY	Seriou Assault nc resulting i injur

part c (Challenge)

Download the data at: https://www.kaggle.com/jolasa/waves-measuring-buoys-data-mooloolaba (https://www.kaggle.com/jolasa/waves-measuring-buoys-data-mooloolaba)

In [35]:

```
waves_df = pd.read_csv('waves.csv')
```

what is the max of Hs, Hmax, Tz, Tp, sst

- hs: Significant wave height, an average of the highest third of the waves in a record
- hmax: The maximum wave height in the record
- tz: The zero upcrossing wave period
- tp: The peak energy wave period
- peak direction: Direction (related to true north) from which the peak period waves are coming from
- sst: Approximation of sea surface temperature

In [36]:

```
waves_df['Date/Time'] = pd.to_datetime(waves_df['Date/Time'])
waves_df['year'] = waves_df['Date/Time'].dt.year.map(int)
waves_df['month'] = waves_df['Date/Time'].dt.month.map(int)
```

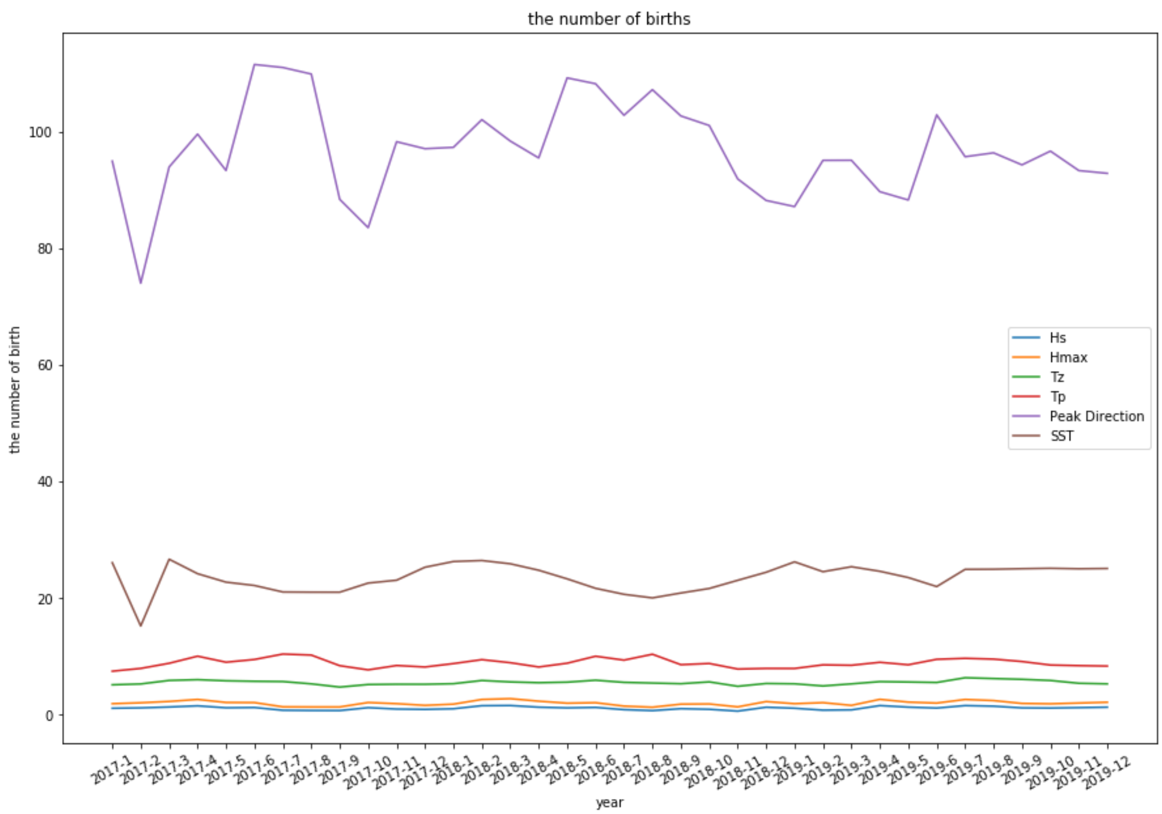
In [37]:

```
waves_mean = waves_df.groupby(['year', 'month']).mean()
waves_mean.reset_index(inplace = True)
```

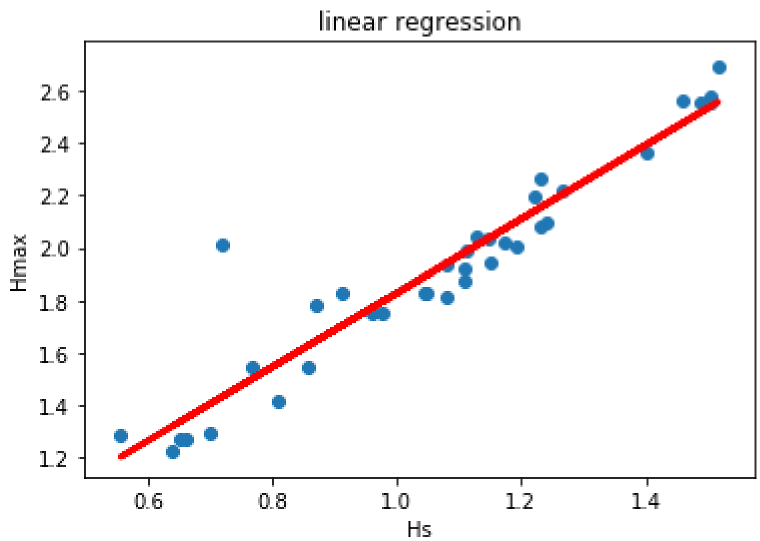
In [38]:
```
waves_mean['year'] = waves_mean['year'].astype(str)
waves_mean['month'] = waves_mean['month'].astype(str)
waves_mean['year_month'] = waves_mean['year'] + '-' + waves_mean['month']
waves_mean.drop('year', axis = 1, inplace = True)
waves_mean.drop('month', axis = 1, inplace = True)
```

In [39]:
```
waves_mean.set_index('year_month', drop = True, inplace = True)
```

In [40]:
```
plt.figure(figsize = (15, 10))
plt.plot(waves_mean)
plt.legend(waves_mean.columns.values)
plt.title('the number of births')
plt.xlabel('year')
plt.ylabel('the number of birth')
plt.xticks(rotation = 30)
plt.show()
```



In [41]:
```
from scipy.stats import linregress
slope, intercept, r_value, p_value, std_err = linregress(waves_mean['Hs'], wa
line = [slope*xi + intercept for xi in waves_mean['Hs']]
plt.plot(waves_mean['Hs'], line, 'r-', linewidth = 3)
plt.scatter(waves_mean['Hs'], waves_mean['Hmax'])
plt.xlabel('Hs')
plt.ylabel('Hmax')
plt.title('linear regression')
plt.show()
```




```
this linear regression is indicate Hmax and Hs is liner relationship, so we
can predict the Hmax by Hs or predicct the Hs by Hmax
```

In [42]:
```
predict_1 = slope * 3.0 + intercept
print('when Hs is 3, the Hmax is:' + str(predict_1))
```

```
when Hs is 3, the Hmax is:4.649155579792573
```

In [ ]:
```
```