Link to the original data: https://www.kaggle.com/jameslko/gun-violence-data (https://www.kaggle.com/jameslko/gun-violence-data)

We were interested in investigating gun violence in aggregate across the United States, as the issue is important and relevant, but often discussed on a case-by-case basis rather than holistically. The data standardizes incident reports including information related to the types of guns used, people involved, and locations incidents occur. Some of what we discovered was that certain cities like Chicago have significantly more gun violence than other cities, handguns pose more of a problem than assault rifles with regards to the number of people killed, and that some seasons are more deadly than others.

In [30]:
```
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import datetime as dt
import statsmodels.formula.api as smf

data = pd.read_csv('gunViolenceData.csv')

# Since an incident_id uniquely identifies a row, we can use it as an index
data.set_index('incident_id', drop = True, inplace=True)

# Remove irrelevant columns
data.drop([
            'address','incident_url','source_url',
            'participant_name','sources','state_house_district',
            'state_senate_district','incident_url_fields_missing',
            'congressional_district','latitude','longitude'], axis=1, inplace=
True)
```

What is the average number of people killed and injured in a typical incident?

In [31]:
```
print('Average number of injuries:', round(data['n_injured'].mean(), 2))
print('Average number of killed:', round(data['n_killed'].mean(), 2))
```

```
Average number of injuries: 0.49
Average number of killed: 0.25
```

Based on the number of deaths and injuries, what's more deadly, an assault rifle or a handgun?

In [32]:
```
# Classify weapons
handguns = ['Handgun', '9mm', 'Auto', '40 SW', 'Mag',
            '38 Spl', '10mm']
assault_rifles = ['AR-15', 'AK-47']
all_rifles = ['22 LR', '308 Win', '30-30 Win', 'Rifle', '300 Win', '30-06 Spr'
, 'AR-15', 'AK-47' ]
shotguns = ['Shotgun', 'gauge']

handgun_list = []
assault_rifle_list = []
all_rifle_list = []
shotgun_list = []

# Create handguns column
for i in data['gun_type']:
    guncount = 0
    for j in handguns:
        guncount += str(i).count(j)
    handgun_list.append(guncount)

data['handguns_used'] = handgun_list

# Create assault_rifles column
for i in data['gun_type']:
    guncount = 0
    for j in assault_rifles:
        guncount += str(i).count(j)
    assault_rifle_list.append(guncount)

data['assault_rifles_used'] = assault_rifle_list

# Create all_rifles column
for i in data['gun_type']:
    guncount = 0
    for j in all_rifles:
        guncount += str(i).count(j)
    all_rifle_list.append(guncount)

data['all_rifles_used'] = all_rifle_list

# Create shotgun column
for i in data['gun_type']:
    guncount = 0
    for j in shotguns:
        guncount += str(i).count(j)
    shotgun_list.append(guncount)

data['shotguns_used'] = shotgun_list

data
```

Out[32]:

incident_id	date	state	city_or_county	n_killed	n_injured	gun_stolen	
461105	2013-01-01	Pennsylvania	Mckeesport	0	4	NaN	
460726	2013-01-01	California	Hawthorne	1	3	NaN	
478855	2013-01-01	Ohio	Lorain	1	3	0::Unknown||1::Unknown	0::Un
478925	2013-01-05	Colorado	Aurora	4	0	NaN	
478959	2013-01-07	North Carolina	Greensboro	2	2	0::Unknown||1::Unknown	0::Ha
478948	2013-01-07	Oklahoma	Tulsa	4	0	NaN	
479363	2013-01-19	New Mexico	Albuquerque	5	0	0::Unknown||1::Unknown	0:
479374	2013-01-21	Louisiana	New Orleans	0	5	NaN	
479389	2013-01-21	California	Brentwood	0	4	NaN	
492151	2013-01-23	Maryland	Baltimore	1	6	NaN	
491674	2013-01-23	Tennessee	Chattanooga	1	3	0::Unknown	
479413	2013-01-25	Missouri	Saint Louis	1	3	0::Unknown	
479561	2013-01-26	Louisiana	Charenton	2	3	0::Unknown	
479554	2013-01-26	District of Columbia	Washington	0	5	0::Unknown	
479460	2013-01-26	Ohio	Springfield	1	3	NaN	
479573	2013-02-02	Tennessee	Memphis	0	5	0::Unknown	
479580	2013-02-03	California	Yuba (county)	1	3	0::Unknown	
479592	2013-02-07	Illinois	Chicago	0	4	NaN	
479603	2013-02-09	Louisiana	New Orleans	0	4	0::Unknown	
480311	2013-02-11	California	Vallejo	1	4	NaN	
480327	2013-02-11	Delaware	Wilmington	3	2	0::Unknown	
480344	2013-02-12	Utah	Midvale	4	1	NaN	

	date	state	city_or_county	n_killed	n_injured	gun_stolen
incident_id						
480358	2013-02-19	California	Orange (county)	4	3	0::Unknown
480383	2013-02-21	Oklahoma	Tulsa	1	3	NaN
480401	2013-02-22	Michigan	Grand Rapids	0	4	NaN
480407	2013-02-23	California	Lancaster	0	4	NaN
480443	2013-02-24	Georgia	Macon	0	8	NaN
481186	2013-03-02	Louisiana	Shreveport	1	3	NaN
481198	2013-03-03	Georgia	Moultrie	2	2	0::Unknown
481208	2013-03-03	Michigan	Saginaw (county)	0	4	NaN
...	...	...	...	...	...	...
1081936	2018-03-31	Maine	Bangor	0	0	0::Unknown
1081946	2018-03-31	District of Columbia	Washington	0	0	0::Unknown
1081949	2018-03-31	Nevada	Las Vegas	0	0	0::Unknown
1082266	2018-03-31	California	Palmdale	1	0	0::Unknown
1082483	2018-03-31	Texas	Wichita Falls	0	1	0::Unknown
1082486	2018-03-31	Texas	Dallas	0	1	0::Unknown
1083121	2018-03-31	Nevada	Reno	1	0	0::Unknown
1081947	2018-03-31	Nevada	Reno	1	0	0::Unknown
1082089	2018-03-31	California	San Diego	0	0	0::Unknown
1081901	2018-03-31	New York	Rochester	1	0	0::Unknown
1082394	2018-03-31	California	Shafter	0	0	0::Unknown
1082392	2018-03-31	California	Oakland	1	0	0::Unknown
1082057	2018-03-31	Florida	Orlando	0	3	0::Unknown
1082091	2018-03-31	California	Stockton	2	0	0::Unknown

incident_id	date	state	city_or_county	n_killed	n_injured	gun_stolen	
1081719	2018-03-31	North Carolina	Kings Mountain	0	4	0::Unknown	
1082388	2018-03-31	Minnesota	Saint Paul	0	2	0::Unknown	
1082197	2018-03-31	Oklahoma	Guthrie	1	0	0::Unknown	
1082023	2018-03-31	Missouri	Festus	0	1	0::Unknown	
1082226	2018-03-31	Missouri	Saint Clair	0	1	0::Unknown	
1081894	2018-03-31	Missouri	Saint Louis	1	0	0::Unknown	
1082234	2018-03-31	Tennessee	Memphis	0	1	0::Unknown	
1081742	2018-03-31	Michigan	Detroit	0	1	0::Unknown	
1082990	2018-03-31	Wisconsin	Madison	0	0	0::Unknown	
1081752	2018-03-31	Illinois	Chicago	0	1	0::Unknown	
1082061	2018-03-31	Washington	Spokane (Spokane Valley)	0	0	0::Unknown	
1083142	2018-03-31	Louisiana	Rayne	0	0	0::Unknown	
1083139	2018-03-31	Louisiana	Natchitoches	1	0	0::Unknown	
1083151	2018-03-31	Louisiana	Gretna	0	1	0::Unknown	
1082514	2018-03-31	Texas	Houston	1	0	0::Unknown	
1081940	2018-03-31	Maine	Norridgewock	2	0	0::Unknown||1::Unknown	0::H

239677 rows × 21 columns

In [33]:
```
# Create dataframe for weapons percentages.
# The info below uses the subset of data for which weapons information is avai
lable.
weapons_data = data.dropna(subset = ['gun_type']).loc[(data['gun_type'].str.fi
nd('0::Unknown') == -1)]

# Classify weapons percentages
handgun_percent = int(((len(weapons_data.loc[weapons_data['handguns_used'] !=
0]))/(len(weapons_data)))*100)
rifle_percent = int(((len(weapons_data.loc[weapons_data['all_rifles_used'] !=
0]))/(len(weapons_data)))*100)
shotgun_percent = int(((len(weapons_data.loc[weapons_data['shotguns_used'] !=
0]))/(len(weapons_data)))*100)

print('Average number of deaths when handgun is used:',
     round(weapons_data.loc[weapons_data['handguns_used'] != 0]['n_killed'].me
an(), 2))
print('Average number of injured when handgun is used:',
     round(weapons_data.loc[weapons_data['handguns_used'] != 0]['n_injured'].m
ean(), 2))
print('Percentage of incidents involving handgun: ',
      handgun_percent, '%', sep = '')

print('\n')

print('Average number of deaths when rifle is used:',
     round(weapons_data.loc[weapons_data['all_rifles_used'] != 0]['n_killed'].
mean(), 2))
print('Average number of injured when rifle is used:',
     round(weapons_data.loc[weapons_data['all_rifles_used'] != 0]['n_injured']
.mean(), 2))
print('Percentage of incidents involving rifle: ',
      rifle_percent, '%', sep = '')

print('\n')

print('Average number of deaths when Shotgun is used:',
     round(weapons_data.loc[weapons_data['shotguns_used'] != 0]['n_killed'].me
an(), 2))
print('Average number of injured when rifle is used:',
     round(weapons_data.loc[weapons_data['shotguns_used'] != 0]['n_injured'].m
ean(), 2))
print('Fraction of incidents involving rifle: ',
      shotgun_percent, '%', sep = '')
```

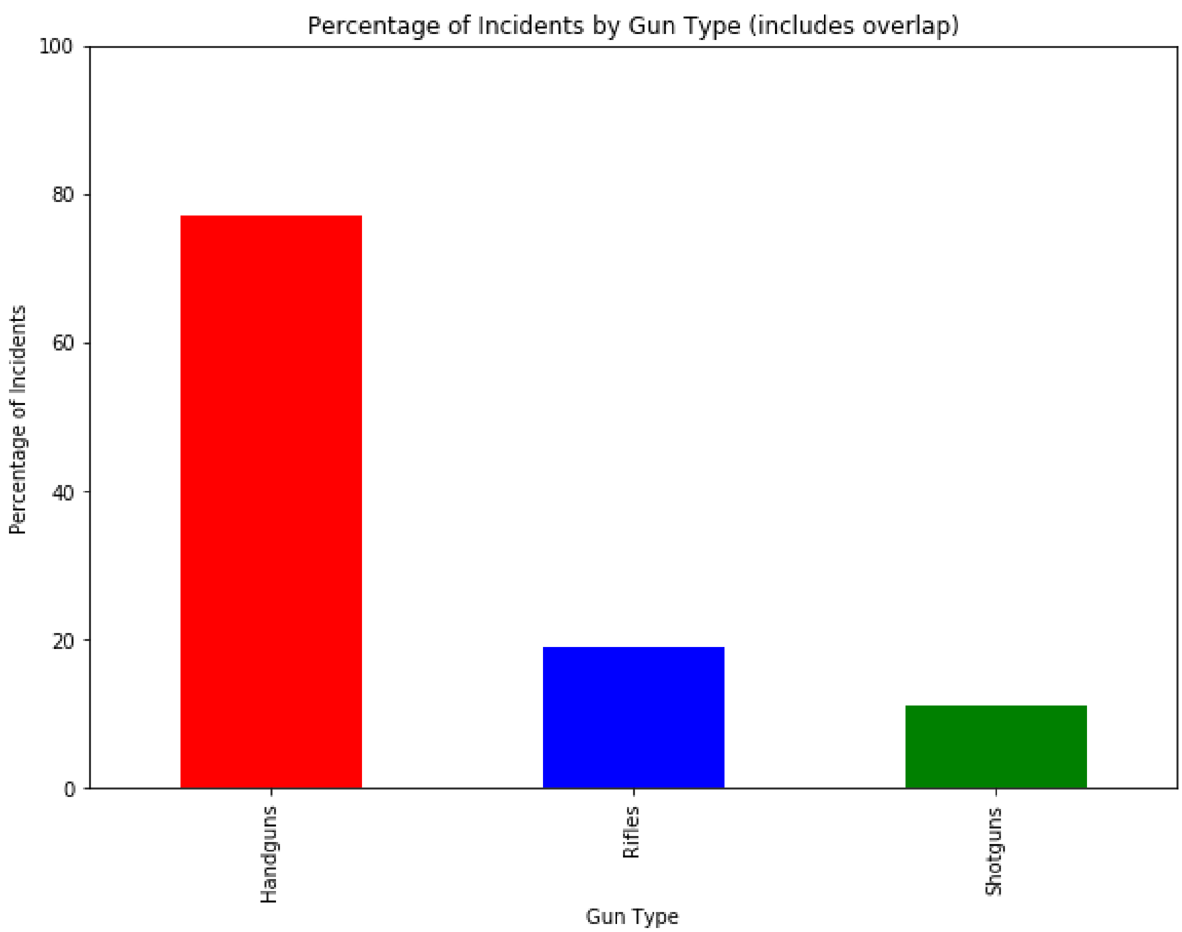
```
Average number of deaths when handgun is used: 0.14
Average number of injured when handgun is used: 0.23
Percentage of incidents involving handgun: 77%


Average number of deaths when rifle is used: 0.18
Average number of injured when rifle is used: 0.25
Percentage of incidents involving rifle: 19%


Average number of deaths when Shotgun is used: 0.17
Average number of injured when rifle is used: 0.24
Fraction of incidents involving rifle: 11%
```

In [34]:

```
weapons_percentage = {'Gun Type': ['Handguns', 'Rifles', 'Shotguns'],
                      'Percentage of Incidents': [handgun_percent, rifle_perce
nt, shotgun_percent]}

weapons_chart = pd.DataFrame(weapons_percentage).set_index('Gun Type')

fig, ax = plt.subplots()
weapons_chart.plot.bar(ax=ax, figsize = (10,7), ylim = (0,100), color = ('r',
'b','g'), legend = False)
ax.set_title('Percentage of Incidents by Gun Type (includes overlap)')
ax.set_ylabel('Percentage of Incidents')
```

Out[34]:

```
Text(0, 0.5, 'Percentage of Incidents')
```

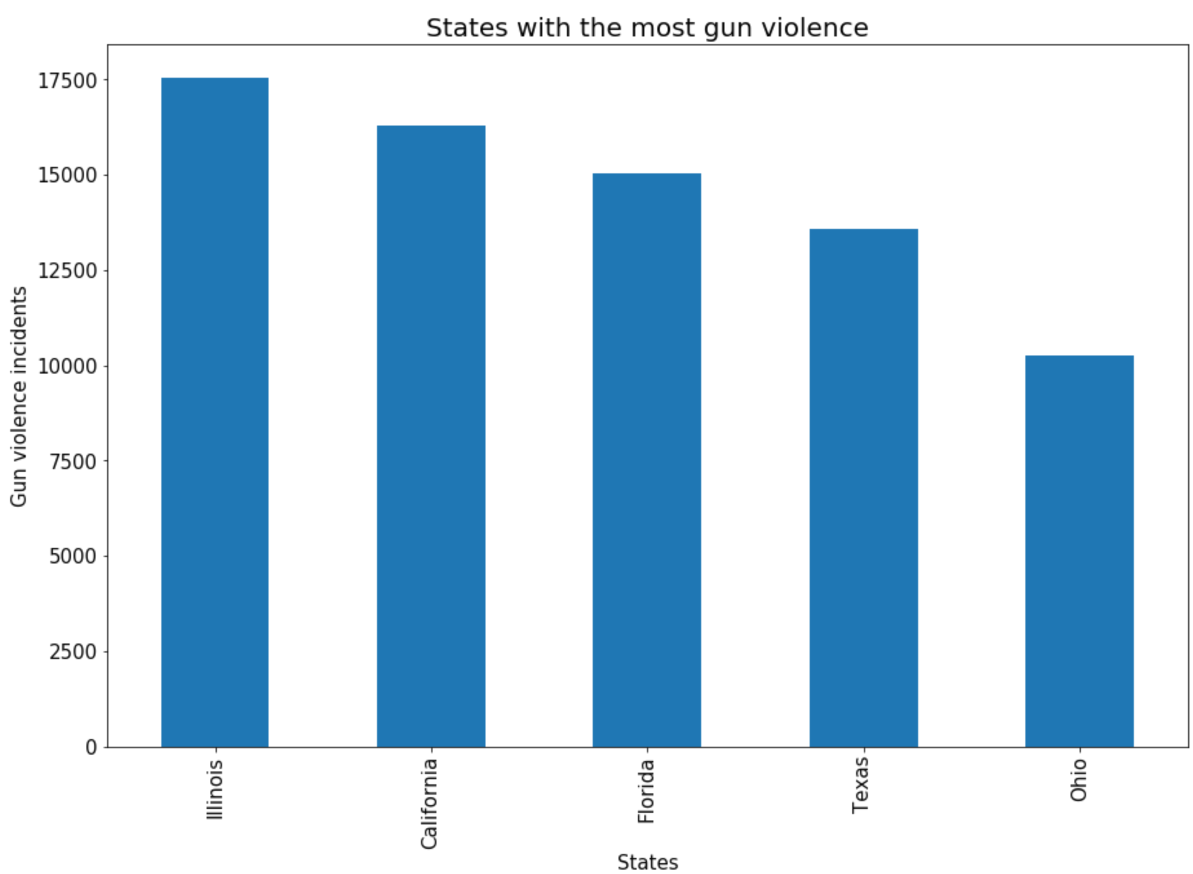


Which states have the most gun violence?

The below shows the five states with the largest number of gun violence incidents. Illinois in particular leads the pack.

In [35]:
```
fig1,ax1 = plt.subplots()
ax1.set_title('States with the most gun violence', size = 20)
ax1.set_xlabel('States', size=15)
ax1.set_ylabel('Gun violence incidents', size=15)
ax1.tick_params(axis='both', labelsize=15)

data['state'].value_counts().head().plot.bar(ax = ax1, figsize = (15,10))
```

Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2314048db00>
```

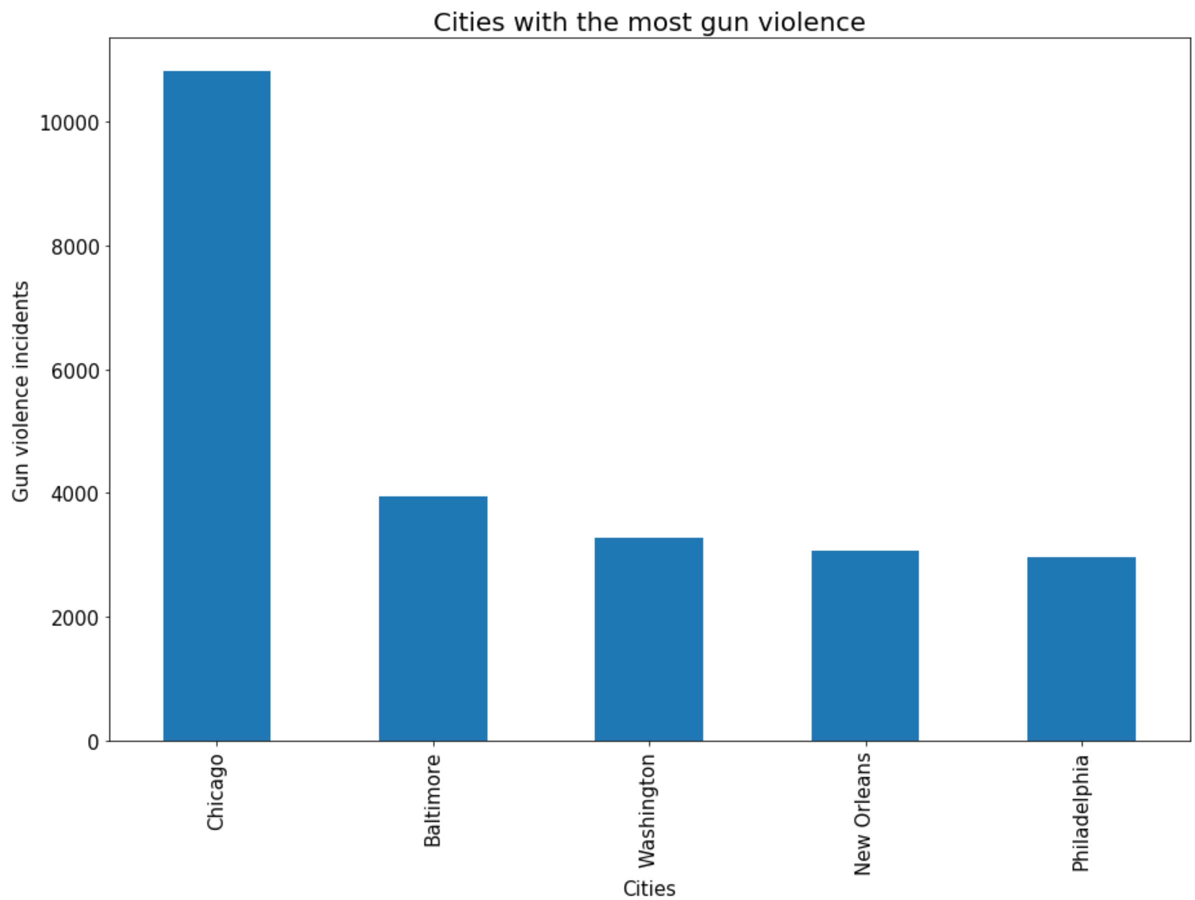


Which cities have the most gun violence?

We can see below that Chicago has the most reported incidents, likely driving Illinois to the top of the back above. Interestingly, the next most violent states do not line up with the next most violent cities. One further area of exploration could be to investigate what leads to diffusion or concentration of gun violence across states.

In [36]:
```
fig2,ax2 = plt.subplots()
ax2.set_title('Cities with the most gun violence', size = 20)
ax2.set_xlabel('Cities', size=15)
ax2.set_ylabel('Gun violence incidents', size=15)
ax2.tick_params(axis='both', labelsize=15)

data['city_or_county'].value_counts().head().plot.bar(ax = ax2, figsize= (15,1
0))

#Follow up: What percentage of gun violence incidents occur in Chicago?
numerator = len(data.loc[data['city_or_county'] == 'Chicago'].index)
denominator = len(data)

percent = (numerator/denominator) * 100

print('Percentage of gun violence incidents that occur in Chicago: ' + str(np.
round(percent, decimals = 2)) + '%')
```

```
Percentage of gun violence incidents that occur in Chicago: 4.51%
```

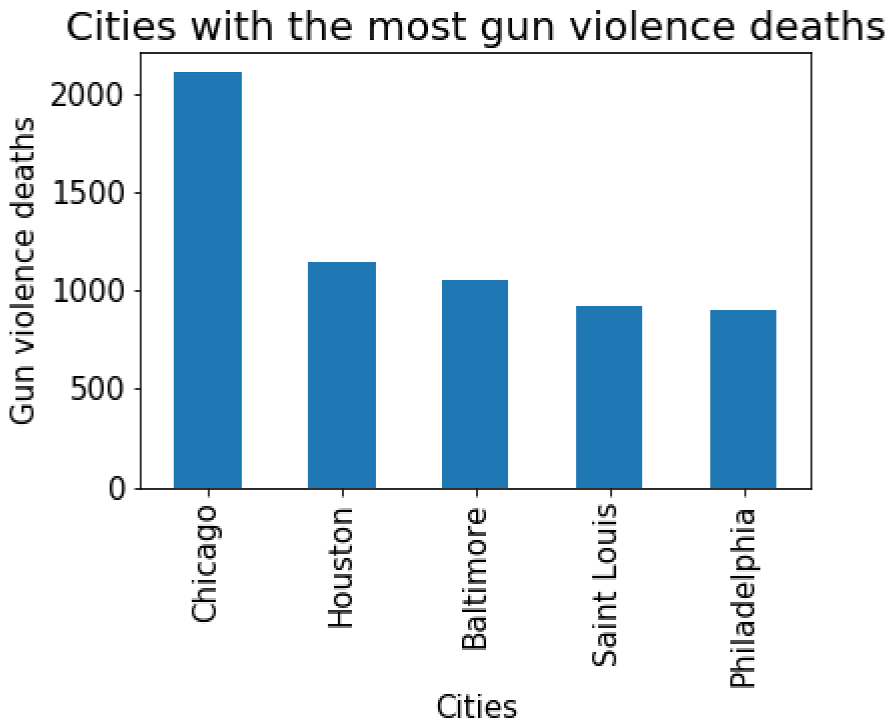


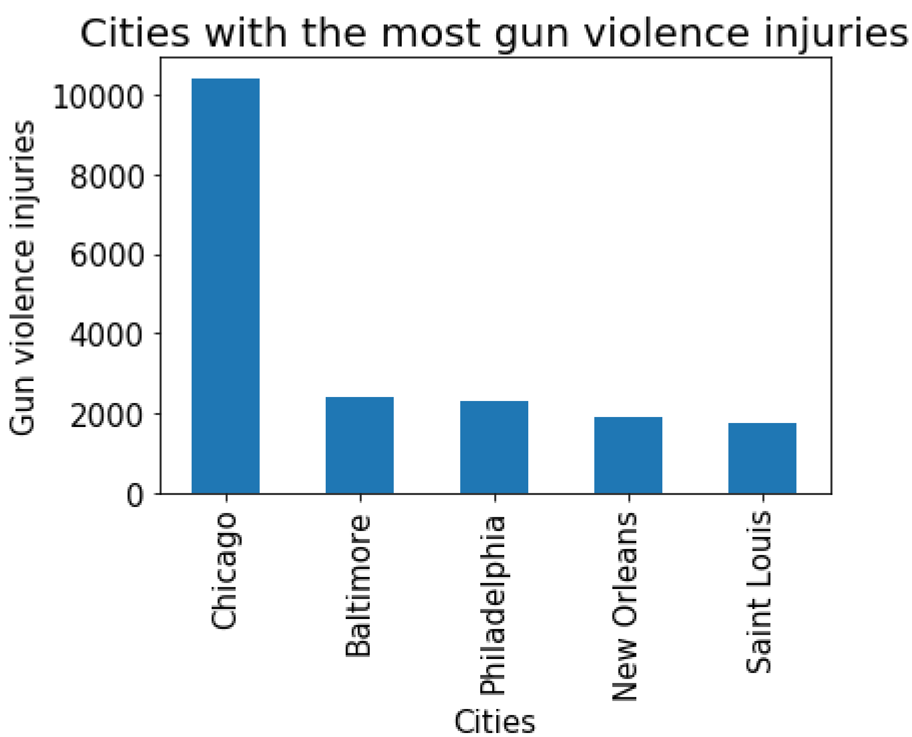
Which cities have the most deaths from gun violence? Injuries?

One question we have is whether incidents of gun violence necessarily correlate strongly with injuries and deaths. The common-sense answer is yes, but is it one-to-one?

In [37]:
```
figMostKilledCities, axMostKilledCities = plt.subplots()
axMostKilledCities.set_title('Cities with the most gun violence deaths', size
= 20)
axMostKilledCities.set_ylabel('Gun violence deaths', size=15)
axMostKilledCities.tick_params(axis='both', labelsize=15)

figMostInjuredCities,axMostInjuredCities = plt.subplots()
axMostInjuredCities.set_title('Cities with the most gun violence injuries', si
ze = 20)
axMostInjuredCities.set_ylabel('Gun violence injuries', size=15)
axMostInjuredCities.tick_params(axis='both', labelsize=15)

casualtyData = data.groupby('city_or_county').sum()

killedData = casualtyData.sort_values(by='n_killed', ascending=False)['n_kille
d']
injuredData = casualtyData.sort_values(by='n_injured', ascending=False)['n_inj
ured']

killedData.head().plot.bar(ax = axMostKilledCities)
injuredData.head().plot.bar(ax = axMostInjuredCities)

axMostInjuredCities.set_xlabel('Cities', size=15)
axMostKilledCities.set_xlabel('Cities', size=15)
```

Out[37]: Text(0.5, 0, 'Cities')





It looks like incidents/injuries/deaths are all correlated, which we show below. A naive conclusion here would be that all gun use is associated with injury and death, but it's important to remember that these are correlations conditional on the incident having been reported to the police. So to make that point fully we'd have to compare gun incidents not reported to police (and probably then expand our definition of "incident") to see if the pattern holds across all gun use.

In [38]:
```
data.groupby('city_or_county').agg({'city_or_county':'count','n_injured':'sum'
,'n_killed':'sum'}).corr()
```

Out[38]:

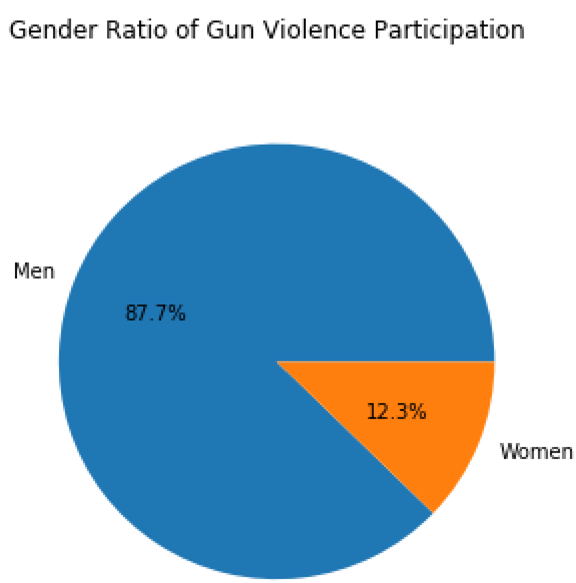
	city_or_county	n_injured	n_killed
city_or_county	1.000000	0.957966	0.942140
n_injured	0.957966	1.000000	0.890021
n_killed	0.942140	0.890021	1.000000

What is the ratio of women to men participants in gun violence?

For every woman involved in a gun violence incident, there are 7.16 men.

In [39]:
```
figGender, axGender = plt.subplots()
participantGenderList = data['participant_gender']
participantGenderList.dropna(inplace=True)

maleCount = 0
femaleCount = 0
for i in participantGenderList:
    femaleCount += i.count('Female')
    maleCount += i.count('Male')

ratio = maleCount/femaleCount
genderRatioDf = pd.DataFrame([np.round(ratio, decimals = 2),1], index=['Men',
'Women'])
genderRatioDf.plot.pie(subplots=True,
                       title ='Gender Ratio of Gun Violence Participation',
                       legend = False,
                       autopct ='%1.1f%%',
                       ax = axGender)
figGender.set_size_inches(5,5)
axGender.set_ylabel('')
```

Out[39]: Text(0, 0.5, '')



Which cities are seeing the largest increase/decrease in gun violence deaths?

We now want to think about gun violence as a time series, it changes rather than levels.

Based on the below findings, it looks like most of the cities that have the largest increases in gun violence deaths are situated in the southeastern/midwestern area. Most of these cities have either no increase in population, or a slight increase in population.

The cities with the largest decreases in population have little to no change in population size and are located in either the northeast or California.

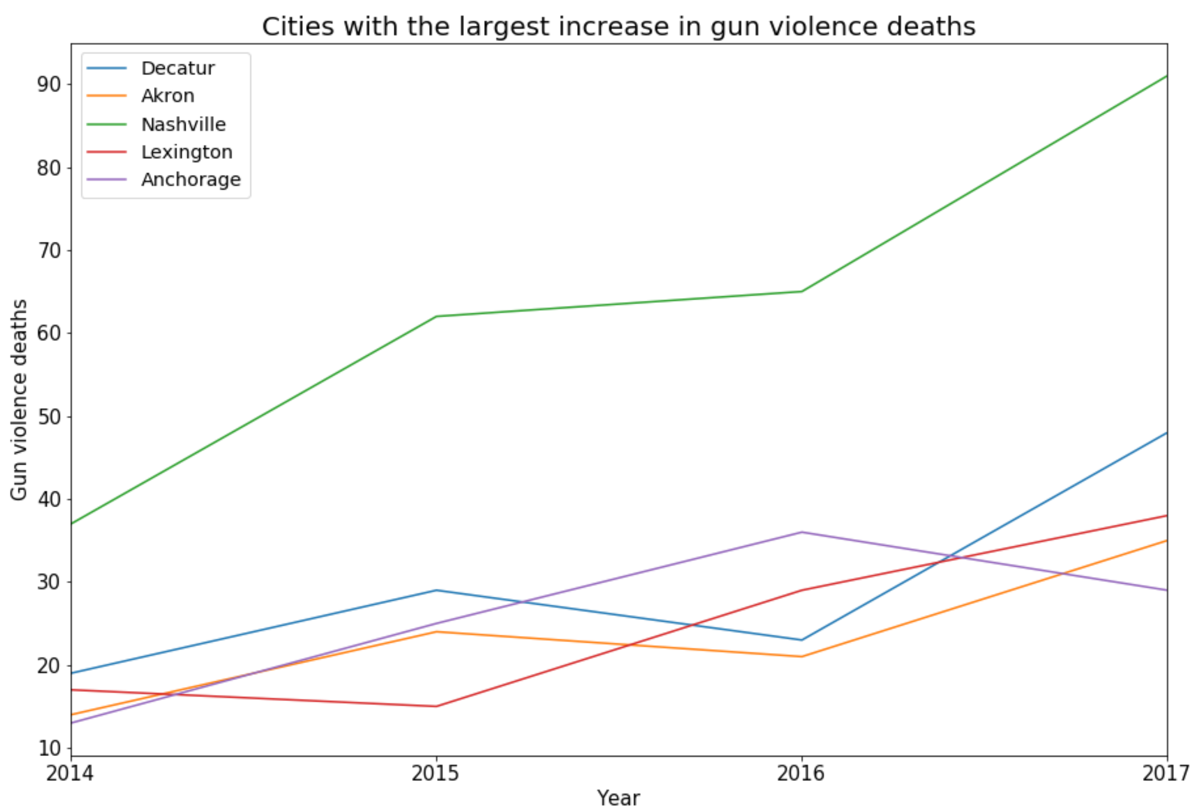
In [40]:
```
#Only consider the cities that have had over 100 gun violence deaths total
killedData > 100

citiesToConsider = killedData[killedData > 100]
citiesToConsider = citiesToConsider.index.tolist()

dataWithFilteredCities = data.loc[data['city_or_county'].isin(citiesToConsider
)]
dataWithFilteredCities['year'] = pd.to_numeric(dataWithFilteredCities['date'].
str[:4])
dataWithFilteredCities = dataWithFilteredCities.loc[~dataWithFilteredCities['y
ear'].isin([2013,2018])]
dataWithFilteredCities = dataWithFilteredCities.groupby(['year','city_or_count
y']).sum()

#For each city, look at the differences in death totals between 2014 and 2017.
# 2014 and 2017 are the first and last full years of data, and that's why the
y're chosen
# (Since 2013 and 2018 have relatively few gun incident entries)
percentageDifferenceInDeaths = []

for i in citiesToConsider:
    query2014 = 'year == 2014 and city_or_county == "'+ i +'"'
    query2017 = 'year == 2017 and city_or_county == "'+ i +'"'
    numKilled2014 = dataWithFilteredCities.query(query2014)['n_killed'].tolist
()
    numKilled2017 = dataWithFilteredCities.query(query2017)['n_killed'].tolist
()
    #Only include cities that have values for the number of people killed in 2
014/2017
    if len(numKilled2014) & len(numKilled2017):
        if numKilled2014[0]:
            #Add the percentage differences in the number of people killed to
 an array
            percentDiff = np.round(100 * (numKilled2017[0] - numKilled2014[0])
/numKilled2014[0], decimals = 2)
            percentageDifferenceInDeaths.append([i, percentDiff])

percentDiffDf = pd.DataFrame(percentageDifferenceInDeaths , columns=['city',
'percentDiff'])

percentDiffDf.sort_values(by='percentDiff', ascending = False, inplace = True)
citiesWithMostIncrease = percentDiffDf.head()['city'].tolist()
citiesWithMostDecrease = percentDiffDf.tail()['city'].tolist()

figIncreasedCities,axIncreasedCities = plt.subplots()
axIncreasedCities.set_title('Cities with the largest increase in gun violence
 deaths', size = 20)
axIncreasedCities.set_ylabel('Gun violence deaths', size=15)
axIncreasedCities.tick_params(axis='both', labelsize=15)

figDecreasedCities,axDecreasedCities = plt.subplots()
axDecreasedCities.set_title('Cities with the largest decrease in gun violence
 deaths', size = 20)
axDecreasedCities.set_ylabel('Gun violence deaths', size=15)
```

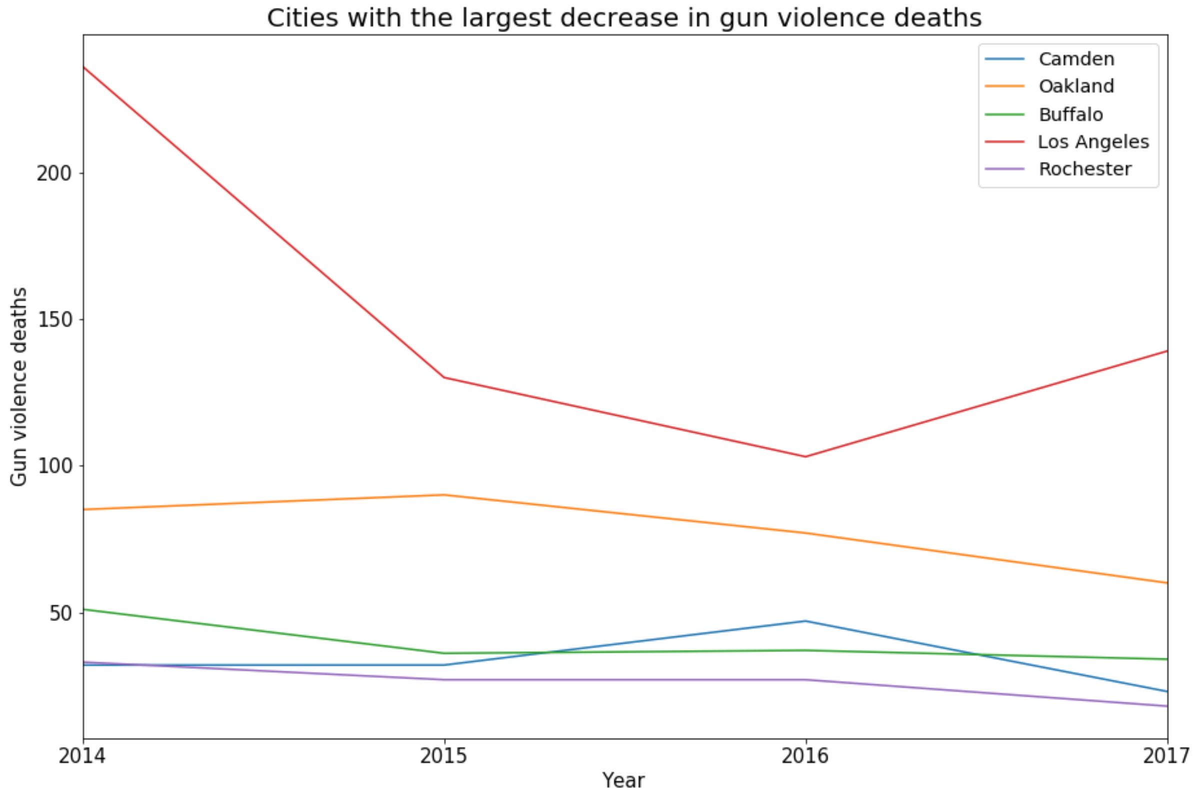
```
axDecreasedCities.tick_params(axis='both', labelsize=15)

for i in citiesWithMostIncrease:
    display(dataWithFilteredCities.query('city_or_county == "' + i + '"')['n_k
illed'].plot(ax = axIncreasedCities,

figsize=(15,10),

legend = True,

label = i))
for i in citiesWithMostDecrease:
    display(dataWithFilteredCities.query('city_or_county == "' + i + '"')['n_k
illed'].plot(ax = axDecreasedCities,

figsize=(15,10),

legend = True,

label = i))
# Set the x-ticks appropriately
xtickYears = ['2014','2015','2016','2017']
xtickPositions = np.array([0,1,2,3])
axIncreasedCities.set_xticks(xtickPositions)
axDecreasedCities.set_xticks(xtickPositions)
axIncreasedCities.set_xticklabels(xtickYears)
axDecreasedCities.set_xticklabels(xtickYears)
axIncreasedCities.set_xlabel('Year', size=15)
axDecreasedCities.set_xlabel('Year', size=15)

axIncreasedCities.legend(fontsize='x-large')
axDecreasedCities.legend(fontsize='x-large')
```

```
C:\Users\romne\Anaconda3\lib\site-packages\ipykernel_launcher.py:8: SettingWi
thCopyWarning:
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-docs/st
able/indexing.html#indexing-view-versus-copy
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2312a335208>

<matplotlib.axes._subplots.AxesSubplot at 0x2312a335208>

<matplotlib.axes._subplots.AxesSubplot at 0x2312a335208>

<matplotlib.axes._subplots.AxesSubplot at 0x2312a335208>

<matplotlib.axes._subplots.AxesSubplot at 0x2312a335208>

<matplotlib.axes._subplots.AxesSubplot at 0x2312b2c1dd8>

<matplotlib.axes._subplots.AxesSubplot at 0x2312b2c1dd8>

<matplotlib.axes._subplots.AxesSubplot at 0x2312b2c1dd8>

<matplotlib.axes._subplots.AxesSubplot at 0x2312b2c1dd8>

<matplotlib.axes._subplots.AxesSubplot at 0x2312b2c1dd8>
```

Out[40]:
```
<matplotlib.legend.Legend at 0x2312be69128>
```





What percentage of total deaths occur in the most dangerous cities?

In [41]:
```
cities = data.groupby('city_or_county', as_index = False).agg(
    {'date':'count', 'n_killed':'sum'}).sort_values(
    by = 'n_killed', ascending = False).rename(columns = {'date':'incidents'})
.set_index('city_or_county')

cities['percentage of total killed'] = np.round(cities['n_killed']/(len(data))
*100, decimals = 2)

cities.iloc[:10,:]
```

Out[41]:

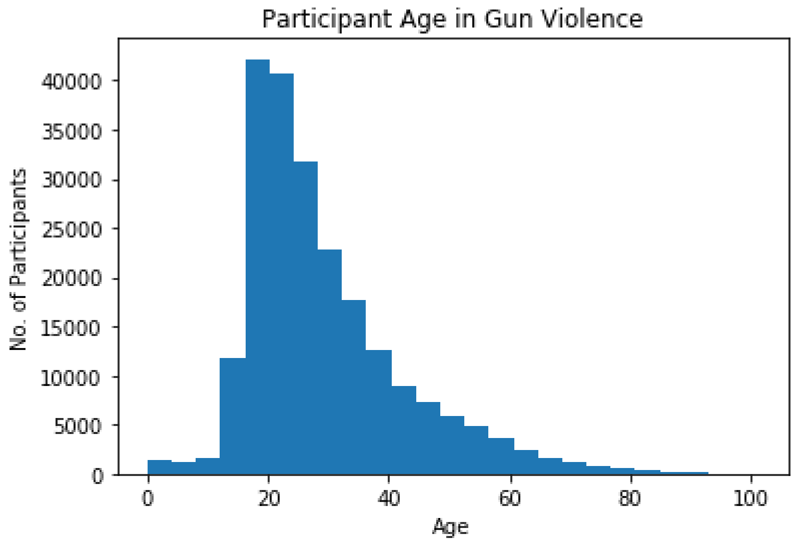
city_or_county	incidents	n_killed	percentage of total killed
Chicago	10814	2104	0.88
Houston	2501	1145	0.48
Baltimore	3943	1055	0.44
Saint Louis	2501	919	0.38
Philadelphia	2963	901	0.38
New Orleans	3071	703	0.29
Los Angeles	1066	636	0.27
Memphis	2386	623	0.26
Indianapolis	1920	616	0.26
Detroit	1834	604	0.25

What is the average participant age?

In [42]:
```
figAge, axAge = plt.subplots()

totalAge = 0
totalParticipants = 0
ageArray = []
#This method takes in a string list
# (for example, the string from participant_age_group: '0::Adult 18+||1::Adult 
18+||2::Adult 18+||3::Adult 18+||4::Adult 18+'
#  returns a list ['Adult 18+', 'Adult 18+', 'Adult 18+', 'Adult 18+', 'Adult
 18+'])
def convertStringList(givenStr):
    #Some strings are formatted incorrectly: with only one ':' and '|'. Ex: 0:
47|1:34|2:34
    isIncorrectMultiple = (givenStr.count('||') == 0) & (givenStr.count('|') > 
0)
    isIncorrectSingle = (givenStr.count(':') == 1) & (givenStr.count('|') == 0
)

    if isIncorrectSingle or isIncorrectMultiple:
        givenStr = givenStr.replace(':','::')
        givenStr = givenStr.replace('|','||')

    constructedList = givenStr.split('||')
    for i in range(0, len(constructedList)):
        strToReplace = constructedList[i]
        index = strToReplace.index('::') + 2
        constructedList[i] = strToReplace[index:]

    return constructedList

for i in data['participant_age']:
    if pd.isnull(i) == False:
        ageList = convertStringList(i)
        totalParticipants += len(ageList)
        for j in ageList:
            #There are invalid dates in the data (possibly incorrect entries t
yped in)
            #Adjust the code in these cases
            if int(j) > 110:
                totalParticipants-=1
            else:
                totalAge += int(j)
                ageArray.append(int(j))

averageAge = np.round(totalAge / totalParticipants, decimals = 2)
print('The average age of participants is: ' + str(averageAge))

plt.hist(x=ageArray, bins = 25)
plt.xlabel('Age')
plt.ylabel('No. of Participants')
plt.title('Participant Age in Gun Violence')
```

```
The average age of participants is: 29.46
```

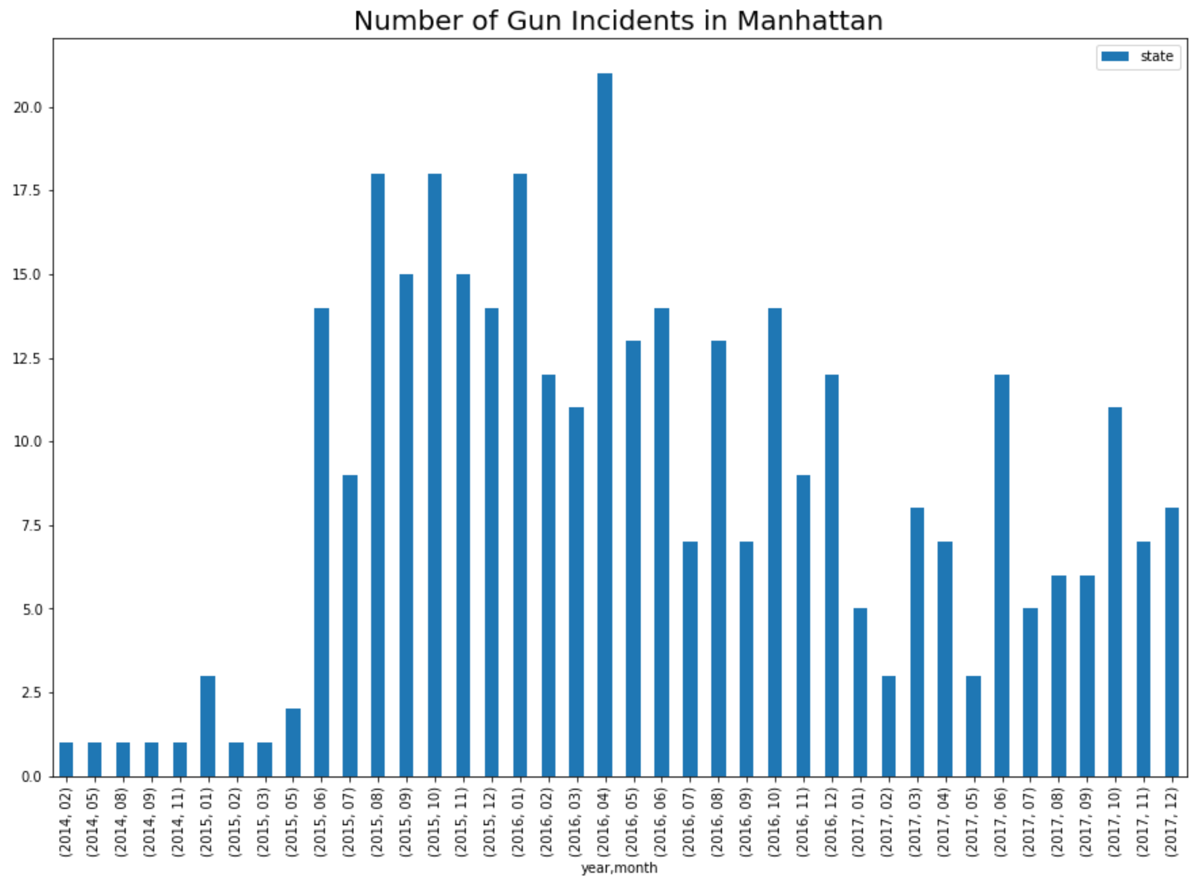
Out[42]:
```
Text(0.5, 1.0, 'Participant Age in Gun Violence')
```



Let's take a monthly look at Manhattan violence, and Chicago violence.

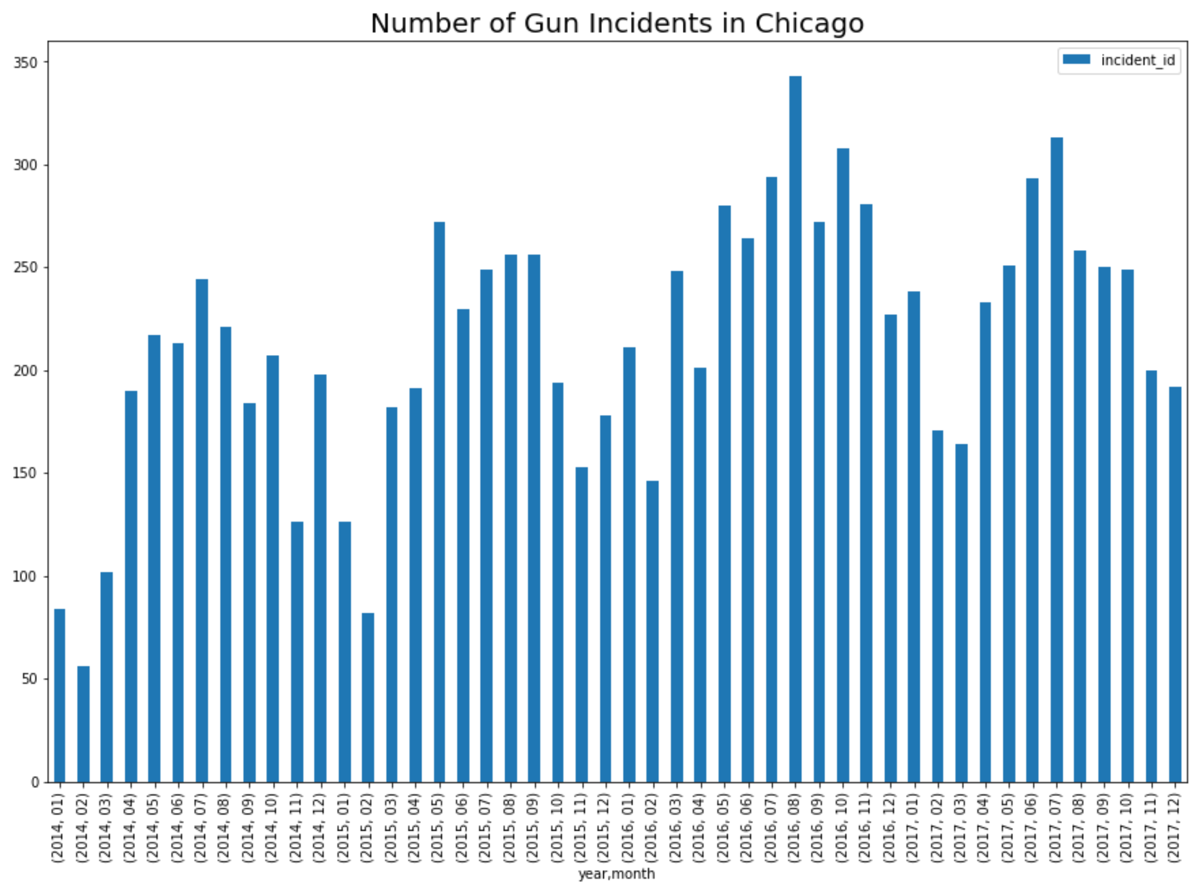
In [43]:
```
data['year'] = data['date'].str[0:4]
data['month'] = data['date'].str[5:7]
drange = ["2014","2015","2016","2017"]

d1 = data.reset_index()
fig,ax = plt.subplots()
ax.set_title('Number of Gun Incidents in Manhattan', size=20)
d1.loc[(d1['city_or_county']=='New York (Manhattan)')&(d1['year'].isin(drange
))].groupby(['year','month']).agg({'state':'count'}).plot.bar(ax=ax, figsize=(
15,10))
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x23122a75160>



In [44]:
```
drange = ["2014","2015","2016","2017"]
fig,ax = plt.subplots()
ax.set_title('Number of Gun Incidents in Chicago', size=20)
d1.loc[(d1['city_or_county']=='Chicago')&(d1['year'].isin(drange))].groupby([
'year','month']).agg({'incident_id':'count'}).plot.bar(ax=ax, figsize=(15,10))
```

Out[44]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2313f8dfac8>
```

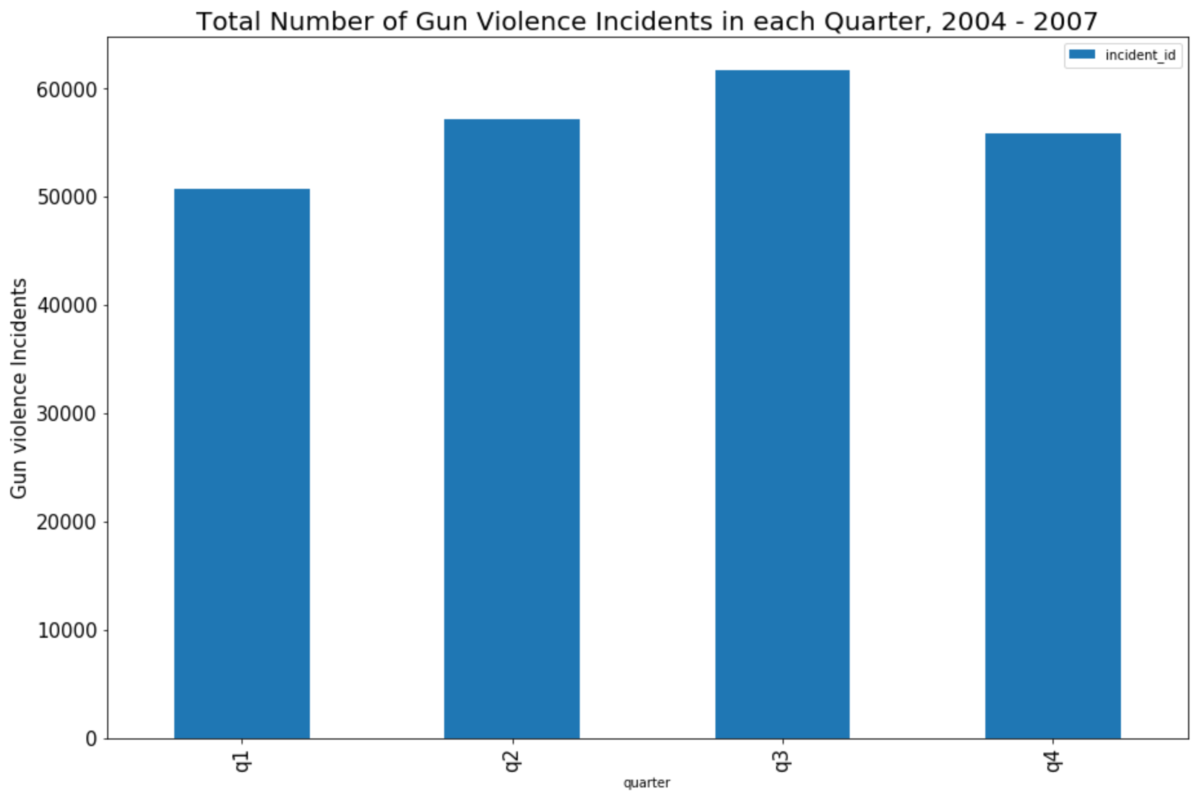


While violence in Chicago exceeds violence in Manhattan, we can see a sort of oscillating pattern in the data for both cities. We've all heard the phrase that gun violence correlates with ice cream sales (the latent variable being heat - let's run a regression to test this. We create dummy variables per quarter and assume for now that Q2 and Q3 are the "summer" quarters while Q1 and Q4 are the "winter" quarters, and aggregate across quarters.

In [45]:
```
conditions = [
    (d1['month'].str.contains('01'))|(d1['month'].str.contains('02'))|(d1['mon
th'].str.contains('03')),
    (d1['month'].str.contains('04'))|(d1['month'].str.contains('05'))|(d1['mon
th'].str.contains('06')),
    (d1['month'].str.contains('07'))|(d1['month'].str.contains('08'))|(d1['mon
th'].str.contains('09')),
    (d1['month'].str.contains('10'))|(d1['month'].str.contains('11'))|(d1['mon
th'].str.contains('12')),
]

choices=['q1','q2','q3','q4']
d1['quarter'] = np.select(conditions,choices,default='missing')
```

In [46]:
```
drange = ["2014","2015","2016","2017"]
fig,ax = plt.subplots()
ax.set_title("Total Number of Gun Violence Incidents in each Quarter, 2004 - 2
007", size = 20)
ax.set_ylabel('Gun violence Incidents', size=15)
ax.tick_params(axis='both', labelsize=15)
d1.loc[(d1['year'].isin(drange))].groupby('quarter').agg({'incident_id':'coun
t'}).plot.bar(ax=ax, figsize=(15,10))
```

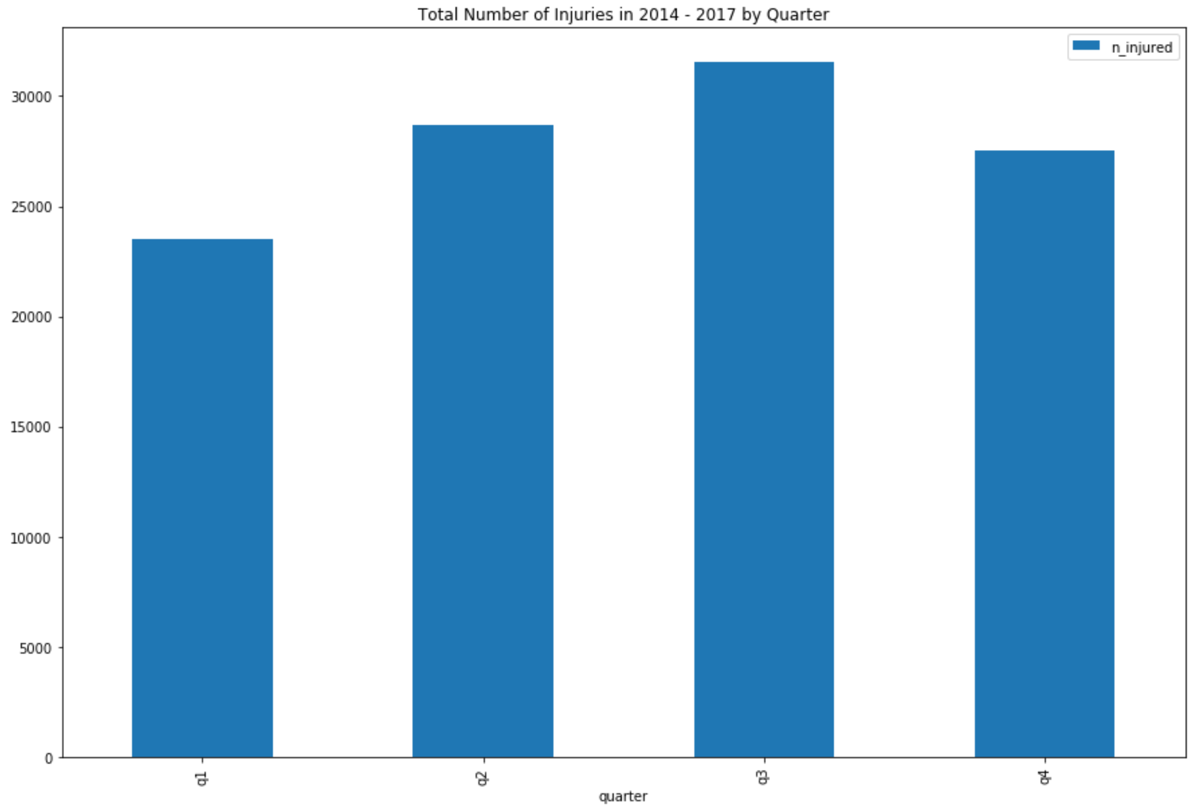
Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x23125be3d30>



We already know that gun incidents correlate with violence and deaths, but let's check if this holds up across "seasons":

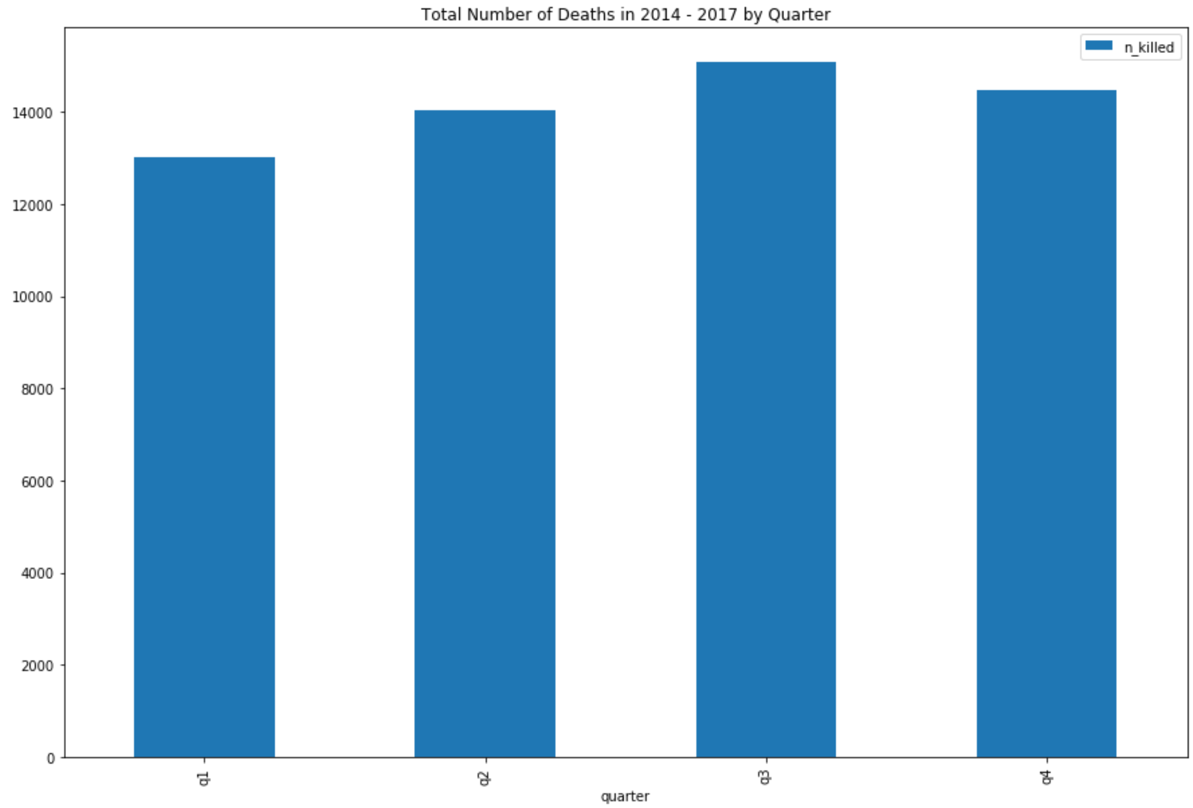
In [47]:
```
drange = ["2014","2015","2016","2017"]
fig,ax = plt.subplots()
ax.set_title("Total Number of Injuries in 2014 - 2017 by Quarter")
d1.loc[(d1['year'].isin(drange))].groupby('quarter').agg({'n_injured':'sum'}).
plot.bar(ax=ax, figsize=(15,10))
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x2311df360f0>



In [48]:
```
drange = ["2014","2015","2016","2017"]
fig,ax = plt.subplots()
ax.set_title("Total Number of Deaths in 2014 - 2017 by Quarter")
d1.loc[(d1['year'].isin(drange))].groupby('quarter').agg({'n_killed':'sum'}).plot.bar(ax=ax, figsize=(15,10))
```

Out[48]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2311e0adb38>
```



Let's use a regression to see if there is a statistically significant effect of entering summer months on the likelihood of gun incidents.

In [54]:
```
d1['dt'] = d1['year'] + '-' + d1['month'] + '-01'
d2 = d1.loc[(d1['year'].isin(drange))].groupby(['city_or_county','dt']).agg({
'incident_id':'count'})
d2.reset_index(inplace=True)
```

In [55]:
```
d2['month'] = d2.reset_index()['dt'].str[5:7]
d2.columns
```

Out[55]:
```
Index(['city_or_county', 'dt', 'incident_id', 'month'], dtype='object')
```

In [56]:
```
d2['q1'] = (d2['month'] == '01')|(d2['month'] == '02')|(d2['month'] == '03')
d2['q2'] = (d2['month'] == '04')|(d2['month'] == '05')|(d2['month'] == '06')
d2['q3'] = (d2['month'] == '07')|(d2['month'] == '08')|(d2['month'] == '09')
d2.set_index(['city_or_county',pd.DatetimeIndex(d2['dt'])],inplace=True)
```

In [57]:
```
reg = smf.ols('incident_id ~ q1 + q2 + q3', data=d2).fit()
```

In [58]:
```
reg.summary()
```

Out[58]:

OLS Regression Results

Dep. Variable:	incident_id	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	7.523
Date:	Tue, 09 Jul 2019	**Prob (F-statistic):**	4.98e-05
Time:	22:41:57	**Log-Likelihood:**	-2.4967e+05
No. Observations:	69122	**AIC:**	4.994e+05
Df Residuals:	69118	**BIC:**	4.994e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	3.1950	0.068	47.149	0.000	3.062	3.328
q1[T.True]	-0.1674	0.097	-1.728	0.084	-0.357	0.022
q2[T.True]	0.1853	0.097	1.917	0.055	-0.004	0.375
q3[T.True]	0.2464	0.095	2.587	0.010	0.060	0.433

Omnibus:	131467.104	**Durbin-Watson:**	0.155
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	351423899.575
Skew:	14.673	**Prob(JB):**	0.00
Kurtosis:	351.077	**Cond. No.**	4.77

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

This is not an impressive r^2, which isn't surprising. Let's see if we can control for heterogeneity across cities/counties by de-meaning the LHS variable (note: Python has dropped the PanelOLS method as of Version 3. We're estimating a loose interpretation of a fixed-effects model here.)

In [59]:
```
d2.drop('dt',1,inplace=True)
```

In [60]:
```
d2.reset_index(inplace=True)
d2['dmy'] = d2['incident_id'] - d2.groupby('city_or_county')['incident_id'].tr
ansform('mean')
```

In [28]:
```
reg = smf.ols('dmy ~ q1 + q2 + q3', data=d2).fit()
```

In [61]:
```
reg.summary()
```

Out[61]:

OLS Regression Results

Dep. Variable:	incident_id	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	7.523
Date:	Tue, 09 Jul 2019	**Prob (F-statistic):**	4.98e-05
Time:	22:42:11	**Log-Likelihood:**	-2.4967e+05
No. Observations:	69122	**AIC:**	4.994e+05
Df Residuals:	69118	**BIC:**	4.994e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3.1950	0.068	47.149	0.000	3.062	3.328
q1[T.True]	-0.1674	0.097	-1.728	0.084	-0.357	0.022
q2[T.True]	0.1853	0.097	1.917	0.055	-0.004	0.375
q3[T.True]	0.2464	0.095	2.587	0.010	0.060	0.433

Omnibus:	131467.104	**Durbin-Watson:**	0.155
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	351423899.575
Skew:	14.673	**Prob(JB):**	0.00
Kurtosis:	351.077	**Cond. No.**	4.77

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

So that helps a bit. We'd likely have to use other data like micro- and macroeconomic factors that could contribute to violence, or person-specific factors that could contribute to the likelihood of participating in gun violence to get a better fit/r^2 - fundamentally, we don't expect seasonality to explain variation in incidents. But we do see that gun incidents increase in the hotter months.