Hampshire Crime Analysis

My local town, Havant is the second safest major town in Hampshire, and is the 30th most dangerous overall out of Hampshire's 268 towns, villages, and cities. The overall crime rate in Havant in 2023 was 93 crimes per 1,000 people. This compares poorly to Hampshire's overall crime rate, coming in 14% higher than the Hampshire rate of 81 per 1,000 daytime population. For England, Wales, and Northern Ireland as a whole, Havant is the 30th safest major town, and the 1,281st most dangerous location out of all towns, cities, and villages.

In January 2024, Havant was the worst major town in Hampshire for drugs, with 35 crimes reported and a crime rate of 0.31 per 1,000 daytime population. January 2024 was also a bad month for Havant residents, when it was Hampshire's most dangerous major town for other crime, recording 14 crimes at a rate of 0.13 per 1,000 daytime population.

The most common crimes in Havant are violence and sexual offences, with 5,092 offences during 2023, giving a crime rate of 46. This is 8% lower than 2022's figure of 5,533 offences and a difference of 3.96 from 2022's crime rate of 50. Havant's least common crime is theft from the person, with 44 offences recorded in 2023, a decrease of 24% from 2022's figure of 58 crimes.

This notebook has a look at the crime stats for all districts in Hampshire as a whole (including 11 districts and two unitary authorities) to see if there are any patterns or interesting insights. We will then home in on Havant to see if we can conclude anything about the crimes reported in this town.

Crimes

- Violence and sexual offences - homicide, violence with and without injury, rape and other sexual offences
- Robbery - of business and personal property
- Theft - burglary in dwelling or other building, vehicles, person, bicycle, shoplifting, all others
- Criminal damage and arson
- Drugs - trafficking and possession
- Possession of weapons
- Public order
- Other miscellaneous offences

Data Sources:

Crime Tree

Hampshire Reported Street Crimes

Crime and Safety Havant

Population - census

Economic Indicators

Import data

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import glob
from mpl_toolkits.basemap import Basemap
import folium
from folium import plugins
import warnings
```

In [2]:
```
warnings.filterwarnings("ignore")
```

In [3]:
```
# Set path to get data

path = r'C:\Users\imoge\AllMLProjects\Data\HantsCrime'

all_files = glob.glob(path + "/*.csv")
li = []
for filename in all_files:
    df = pd.read_csv(filename, index_col=None, header=0)
    li.append(df)
```

In [4]:
```
# Check we have picked up all the files
len(li)
```

Out[4]: 36

In [5]:
```
# Concat into a dataframe and get the shape
df = pd.concat(li, axis=0, ignore_index=True)
df.shape
```

Out[5]: (565163, 12)

In [6]:
```
df.head()
```

Out[6]:

	Crime ID	Month	Reported by	Falls within	Long
0	NaN	2021-04	Hampshire Constabulary	Hampshire Constabulary	-1.1
1	1e89d22ab70b2fca40c73246e918b7768dbbd747aa23c4...	2021-04	Hampshire Constabulary	Hampshire Constabulary	-1.1

	Crime ID	Month	Reported by	Falls within	Long
2	9ff12e79f8783d9b1d5384db940203c45b4fb0a0368132...	2021-04	Hampshire Constabulary	Hampshire Constabulary	-1.1
3	79c56665e645643bdbd3d563b923f51c1fd3ac059a0d9e...	2021-04	Hampshire Constabulary	Hampshire Constabulary	-1.1
4	cf9c98dd82e6e121c3e255ce7b0d995ebf1062c5623684...	2021-04	Hampshire Constabulary	Hampshire Constabulary	-1.1

Data Cleaning

In [7]:

```
# Check datatypes and null values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 565163 entries, 0 to 565162
Data columns (total 12 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   Crime ID               495724 non-null  object 
 1   Month                  565163 non-null  object 
 2   Reported by            565163 non-null  object 
 3   Falls within           565163 non-null  object 
 4   Longitude              565163 non-null  float64
 5   Latitude               565163 non-null  float64
 6   Location               565163 non-null  object 
 7   LSOA code              565163 non-null  object 
 8   LSOA name              565163 non-null  object 
 9   Crime type             565163 non-null  object 
 10  Last outcome category  495724 non-null  object 
 11  Context                0 non-null       float64
dtypes: float64(3), object(9)
memory usage: 51.7+ MB
```

In [8]:

```
# Check nulls
df.isnull().sum()
```

Out[8]:

```
Crime ID                 69439
Month                        0
Reported by                  0
Falls within                 0
Longitude                    0
Latitude                     0
Location                     0
LSOA code                    0
LSOA name                    0
Crime type                   0
Last outcome category    69439
```

```
Context                    565163
dtype: int64
```

In [9]:

```
# What values do we have in this category
df['Last outcome category'].unique()
```

Out[9]:

```
array([nan, 'Unable to prosecute suspect',
       'Investigation complete; no suspect identified',
       'Status update unavailable', 'Local resolution',
       'Offender given a caution',
       'Further action is not in the public interest',
       'Awaiting court outcome', 'Court result unavailable',
       'Further investigation is not in the public interest',
       'Formal action is not in the public interest',
       'Action to be taken by another organisation',
       'Suspect charged as part of another case', 'Under investigation'],
      dtype=object)
```

It is not entirely clear why there are so many blanks as there is a category for 'under investigation' and it might be assumed that there should be an outcome for all cases

In [10]:

```
# Lets drop a few columns of no interest
df = df.drop(columns = ['Crime ID','Reported by','Falls within','Context'],axis
```

In [11]:

```
# Change the name of the Month column to date and then replace with a datetime
df.rename(columns = {'Month':'Date'},inplace = True)
df['Date'] = pd.to_datetime(df['Date'])

# Extract year, month and day
df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month
df['Month Name'] = df['Date'].dt.month_name()

# Drop the date column
df.drop(columns = ['Date'],axis = 1, inplace = True)
```

In [12]:

```
df.head()
```

Out[12]:

	Longitude	Latitude	Location	LSOA code	LSOA name	Crime type	Last outcome category	Year	Mo
0	-1.147727	51.353443	On or near The Beeches	E01022553	Basingstoke and Deane 001A	Anti-social behaviour	NaN	2021	
1	-1.147940	51.355909	On or near Bishops Close	E01022553	Basingstoke and Deane 001A	Violence and sexual offences	Unable to prosecute suspect	2021	
2	-1.147940	51.355909	On or near Bishops Close	E01022553	Basingstoke and Deane 001A	Violence and sexual offences	Unable to prosecute suspect	2021	
3	-1.146700	51.353067	On or near	E01022553	Basingstoke and Deane	Violence and	Investigation complete;	2021	

	Longitude	Latitude	Location	LSOA code	LSOA name	Crime type	Last outcome category	Year	Mo
			Carrington Crescent		001A	sexual offences	no suspect identified		
4	-1.147940	51.355909	On or near Bishops Close	E01022553	Basingstoke and Deane 001A	Violence and sexual offences	Unable to prosecute suspect	2021	

In [13]:
```
df.tail()
```

Out[13]:

	Longitude	Latitude	Location	LSOA code	LSOA name	Crime type	Last outcome category	Yea
565158	-1.040917	50.881798	On or near Carey Lane	E01034734	Winchester 014G	Violence and sexual offences	Unable to prosecute suspect	202
565159	-1.047425	50.877058	On or near Newlands Avenue	E01034734	Winchester 014G	Violence and sexual offences	Unable to prosecute suspect	202
565160	-1.048837	50.871224	On or near Marrelsmoor Avenue	E01034734	Winchester 014G	Violence and sexual offences	Investigation complete; no suspect identified	202
565161	-1.048837	50.871224	On or near Marrelsmoor Avenue	E01034734	Winchester 014G	Violence and sexual offences	Under investigation	202
565162	-0.968508	51.361076	On or near Sun Lane	E01016690	Wokingham 017C	Public order	Investigation complete; no suspect identified	202

We have data from April 2021 through to March 2024, so we have two years of complete data, one year with nine months and one year with just three months. We will focus in on 2022 and 2023 and drop the rest of the data from the dataset. We will then be able to average these two years if required.

In [14]:
```
# Get data for 2022 and 2023
df2 = df[(df['Year']==2022) | (df['Year']==2023)]
df2.shape
```

Out[14]:
```
(373440, 10)
```

In [15]:

```
# What unique LSOA names do we have?
df2['LSOA name'].unique()
```

Out[15]:

```
array(['Basingstoke and Deane 001A', 'Basingstoke and Deane 001B',
       'Basingstoke and Deane 001C', ...,
       'Bournemouth, Christchurch and Poole 019C', 'Dorset 007B',
       'Surrey Heath 010B'], dtype=object)
```

It seems as if we have some LSOA names that are not Hampshire. We are interested in those that relate to Hampshire only. Lets have a look at one of these other ones.

In [16]:

```
# Check one of them
df2[df2['LSOA name']=='Guildford 004C']
```

Out[16]:

	Longitude	Latitude	Location	LSOA code	LSOA name	Crime type	Last outcome category	Year	Mont
336435	-0.728433	51.27784	On or near Stratford Road	E01030428	Guildford 004C	Bicycle theft	Investigation complete; no suspect identified	2022	1

Lower Layer Super Output Areas (LSOAs): LSOAs have an average population of 1500 people or 650 households. A lot more data is available directly at LSOA level, including the majority of the data included within our tool, Local Insight.

In [17]:

```
# how many unique codes do we have?
len(list(df2['LSOA code'].unique()))
```

Out[17]:

```
1326
```

Districts:

- Basingstoke & Deane Borough Council
- East Hampshire District Council
- Eastleigh Borough Council
- Fareham Borough Council
- Gosport Borough Council
- Hart District Council
- Havant Borough Council
- New Forest District Council
- Portsmouth City Council
- Rushmoor Borough Council
- Southampton City Council
- Test Valley Borough Council
- Winchester City Council

We can look up the LSOA codes for each of these from here

In [18]:

```
# Read in the LSOA code list file
code_list = pd.read_csv(r'C:\Users\imoge\AllMLProjects\Data\LSOAcodes.csv')
code_list.head(2)
```

Out[18]:

	LSOA11CD	LSOA11NM	LSOA21CD	LSOA21NM	LAD22CD	LAD22NM	LAD22NMW	Objec
0	E01000155	Barnet 030D	E01033916	Barnet 042B	E09000003	Barnet	NaN	
1	E01000305	Barnet 036B	E01000305	Barnet 036B	E09000003	Barnet	NaN	

In [19]:

```
# Check one of the districts
code_list[code_list['LSOA11NM'].str.contains('Basingstoke')].head()
```

Out[19]:

	LSOA11CD	LSOA11NM	LSOA21CD	LSOA21NM	LAD22CD	LAD22NM	LAD22NMW
21603	E01022552	Basingstoke and Deane 014E	E01022552	Basingstoke and Deane 014E	E07000084	Basingstoke and Deane	NaN
21625	E01022553	Basingstoke and Deane 001A	E01022553	Basingstoke and Deane 001A	E07000084	Basingstoke and Deane	NaN
21630	E01022554	Basingstoke and Deane 001B	E01022554	Basingstoke and Deane 001B	E07000084	Basingstoke and Deane	NaN
21636	E01022555	Basingstoke and Deane 001C	E01022555	Basingstoke and Deane 001C	E07000084	Basingstoke and Deane	NaN
21642	E01022556	Basingstoke and Deane 001D	E01022556	Basingstoke and Deane 001D	E07000084	Basingstoke and Deane	NaN

In [20]:

```
# Get the codes for each district [We add in a space for Hart so we don't pick 
basingstoke = list(code_list[code_list['LSOA11NM'].str.contains('Basingstoke')]
easthants = list(code_list[code_list['LSOA11NM'].str.contains('East Hamp')]['LS
eastleigh = list(code_list[code_list['LSOA11NM'].str.contains('Eastleigh')]['LS
fareham = list(code_list[code_list['LSOA11NM'].str.contains('Fareham')]['LSOA11
gosport = list(code_list[code_list['LSOA11NM'].str.contains('Gosport')]['LSOA11
havant = list(code_list[code_list['LSOA11NM'].str.contains('Havant')]['LSOA11CD
newf = list(code_list[code_list['LSOA11NM'].str.contains('New Forest')]['LSOA11
ports = list(code_list[code_list['LSOA11NM'].str.contains('Portsmouth')]['LSOA1
rush = list(code_list[code_list['LSOA11NM'].str.contains('Rushmoor')]['LSOA11CD
south = list(code_list[code_list['LSOA11NM'].str.contains('Southampton')]['LSOA
test = list(code_list[code_list['LSOA11NM'].str.contains('Test Valley')]['LSOA1
winch = list(code_list[code_list['LSOA11NM'].str.contains('Winchester')]['LSOA1
hart = list(code_list[code_list['LSOA11NM'].str.contains('Hart ')]['LSOA11CD'].
```

```
# Add them into one list
districts = basingstoke + easthants + eastleigh + fareham + gosport + havant +
```

In [21]:

```
# Filter the dataframe against this list to give us just the LSOAs we are intere
df_filtered = df2[df2['LSOA code'].isin(districts)]
df_filtered.shape
```

Out[21]:

```
(338917, 10)
```

Some of the questions/issues we might want to ask/investigate based on the data:

- crimes by location (LSOA area and latitude/longitude
- types of crimes in the county overall and by area
- types of crimes by date of report
- outcomes for crimes for the county and by area

Types of crimes

In [22]:

```
# Get unique types of crime
df_filtered['Crime type'].unique()
```

Out[22]:

```
array(['Other theft', 'Public order', 'Violence and sexual offences',
       'Anti-social behaviour', 'Drugs', 'Shoplifting',
       'Theft from the person', 'Criminal damage and arson',
       'Possession of weapons', 'Burglary', 'Vehicle crime',
       'Other crime', 'Bicycle theft', 'Robbery'], dtype=object)
```

We have 14 categories of crime which we can consolidate a bit to make analysis easier.

In [23]:

```
pd.options.mode.chained_assignment = None

# Combine some categories
df_filtered['Crime type'].replace({'Other theft':'Theft',
                                   'Bicycle theft':'Theft',
                                   'Theft from the person':'Theft',
                                   'Public order':'Anti-social & Public Order',
                                   'Anti-social behaviour':'Anti-social & Publi
                                   'Robbery':'Burglary & Robbery',
                                   'Burglary':'Burglary & Robbery'},inplace = T
```

In [24]:

```
# Groupby crime type
crimes = df_filtered.groupby(['Crime type'],as_index = False)['Year'].count().s
crimes['Average'] = crimes['Year']/2
crimes['%'] = crimes['Average']/crimes['Average'].sum()*100
crimes
```

Out[24]:

	Crime type	Year	Average	%
9	Violence and sexual offences	135941	67970.5	40.110411
0	Anti-social & Public Order	73215	36607.5	21.602634
7	Theft	28246	14123.0	8.334194
2	Criminal damage and arson	27214	13607.0	8.029695

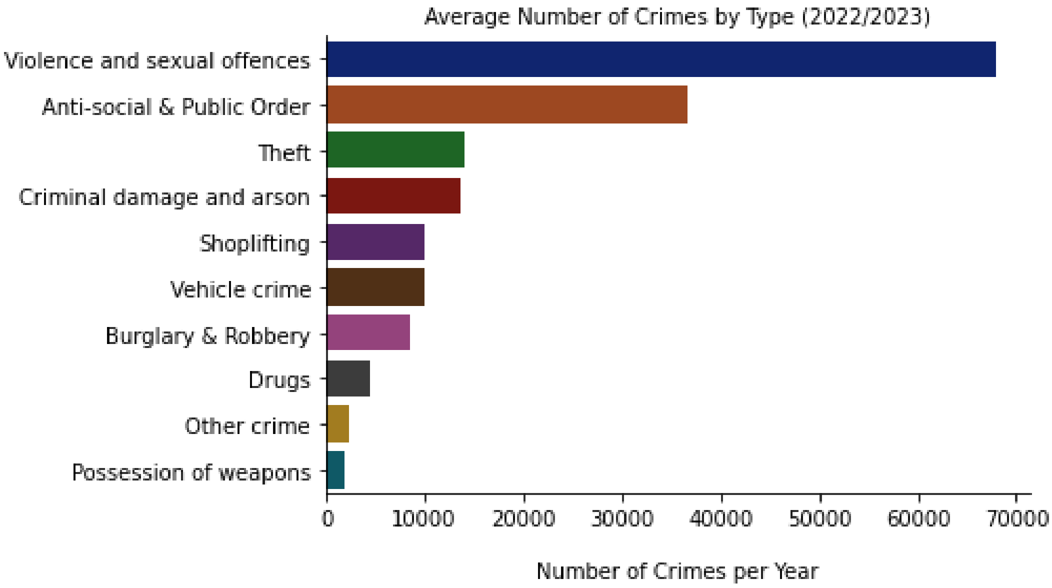
	Crime type	Year	Average	%
6	Shoplifting	20117	10058.5	5.935672
8	Vehicle crime	19938	9969.0	5.882856
1	Burglary & Robbery	16973	8486.5	5.008011
3	Drugs	8785	4392.5	2.592080
4	Other crime	4624	2312.0	1.364346
5	Possession of weapons	3864	1932.0	1.140102

The most commonly occurring crime is violence and sexual offences, with an average of almost 68000 per year accounting for 40% of the total.

violent and sexual crimes include: domestic abuse, rape, sexual offences, stalking, harassment, so-called 'honour-based' violence including forced marriage, female genital mutilation, child abuse, human trafficking focusing on sexual exploitation, prostitution, pornography and obscenity.

In [25]:

```
# Plot the crimes across the county for the two year period
ax = sns.barplot(data = crimes, y = 'Crime type', x = 'Average', palette = 'dar
plt.title('Average Number of Crimes by Type (2022/2023)', fontsize = 10)
plt.ylabel("")
plt.xlabel("Number of Crimes per Year", labelpad = 15)
ax.spines[['right', 'top']].set_visible(False);
```



We can see that violence is the biggest category by far and possession of weapons is the smallest of the reported crimes

In [26]:

```
df_filtered.head()
```

Out[26]:

	Longitude	Latitude	Location	LSOA code	LSOA name	Crime type	Last outcome category	Year
151109	-1.144834	51.353800	On or near Stanfield	E01022553	Basingstoke and Deane 001A	Theft	Unable to prosecute suspect	2022
151110	-1.151854	51.357016	On or near Supermarket	E01022554	Basingstoke and Deane 001B	Anti-social & Public Order	Local resolution	2022
151111	-1.153329	51.357269	On or near The Burrows	E01022554	Basingstoke and Deane 001B	Violence and sexual offences	Unable to prosecute suspect	2022
151112	-1.141741	51.354829	On or near The Parade	E01022555	Basingstoke and Deane 001C	Anti-social & Public Order	NaN	2022
151113	-1.140079	51.350798	On or near Maple Grove	E01022555	Basingstoke and Deane 001C	Anti-social & Public Order	NaN	2022

Types of crimes by year

In [27]:

```
# Does this vary by year?
crimes_year = df_filtered.groupby(['Year','Crime type'],as_index = False)['Mont


crimes_year['%change'] = round((crimes_year[2023] - crimes_year[2022])/crimes_y
crimes_year.sort_values(by = '%change',ascending = False)
```

Out[27]:

Year	2022	2023	%change
Crime type			
Shoplifting	8632	11485	33.1
Drugs	4348	4437	2.0
Possession of weapons	1979	1885	-4.7
Vehicle crime	10395	9543	-8.2
Other crime	2446	2178	-11.0
Criminal damage and arson	14553	12661	-13.0
Theft	15194	13052	-14.1
Violence and sexual offences	73700	62241	-15.5
Burglary & Robbery	9453	7520	-20.4

Year	2022	2023	%change
Crime type			
Anti-social & Public Order	41339	31876	-22.9

This table highlights some interesting changes between 2022 and 2023. Shoplifting as a crime has seen a 33% increase in reports whereas all of the other crimes bar drugs have reduced over the period.

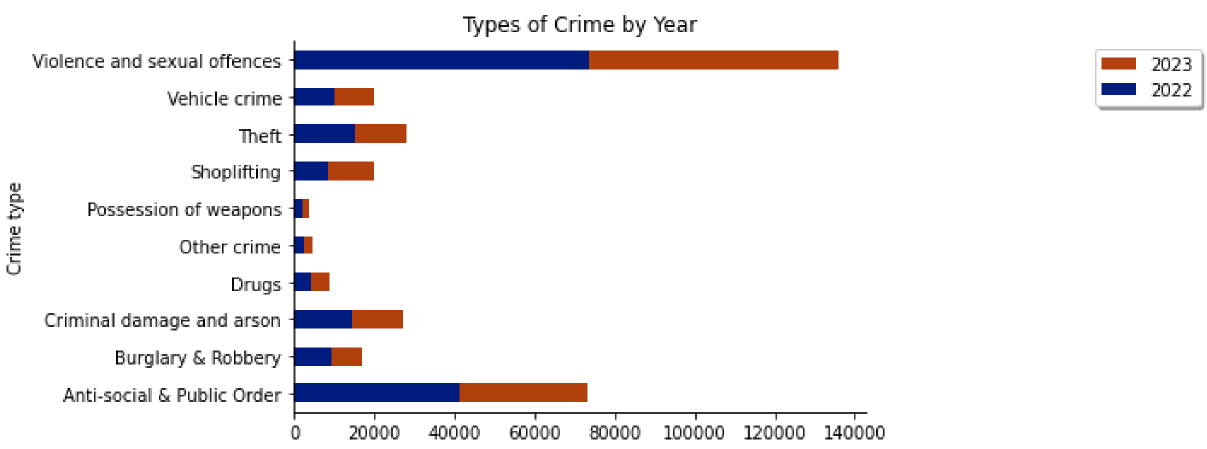
This is interesting as anecdotally, shops in my local town have been reporting significant increases in shoplifting, with one shop off-licence locking doors and only opening them when a customer approaches.

In the nearest city, this increase has been reported in the news and it would be interesting to have a look at which towns and cities are impacted by this the most.

Portsmouth News Article

In [28]:

```
# Plot chart
sns.set_palette('dark')
ax = crimes_year[[2022,2023]].plot(kind = 'barh',stacked = True)

# Add titles
plt.title('Types of Crime by Year')
plt.xlabel("")

# Remove frames
ax.spines[['right', 'top']].set_visible(False)

# Legend
handles, labels = ax.get_legend_handles_labels()
ax.legend(reversed(handles), reversed(labels),loc='upper right', bbox_to_anchor
          ncol=1, fancybox=True, shadow=True);
```



Types of crimes by month

Does the pattern of total crime vary by month?

Does the pattern of different types of crime vary by month?

In [29]:

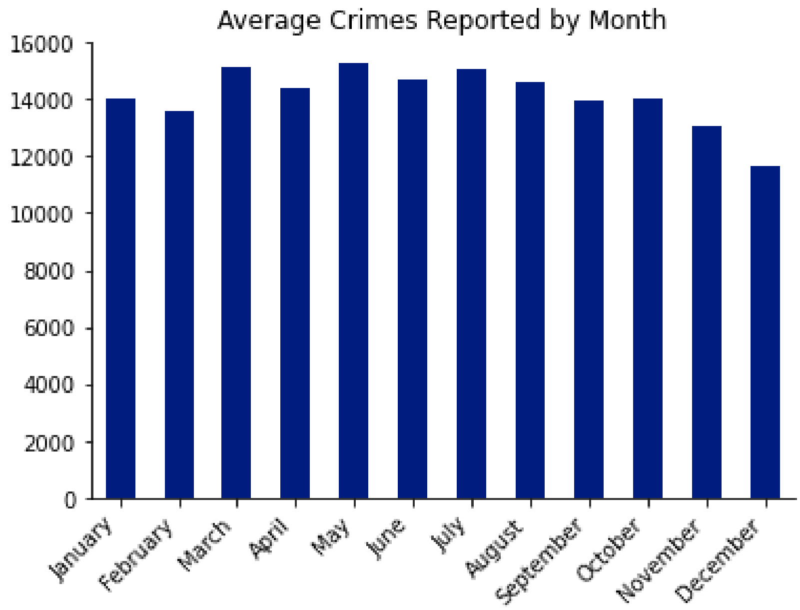
```
months = list(df_filtered['Month Name'].unique())
crime_month = df_filtered.groupby(['Month'],as_index = False)['Year'].count()
crime_month.index = months
crime_month['Average'] = crime_month['Year']/2
crime_month.sort_values(by = 'Average',ascending = False)
```

Out[29]:

	Month	Year	Average
May	5	30558	15279.0
March	3	30271	15135.5
July	7	30112	15056.0
June	6	29381	14690.5
August	8	29182	14591.0
April	4	28819	14409.5
January	1	28085	14042.5
October	10	28068	14034.0
September	9	27945	13972.5
February	2	27156	13578.0
November	11	26088	13044.0
December	12	23252	11626.0

In [30]:

```
# Plot crimes by month
ax = crime_month['Average'].plot(kind = 'bar')
plt.title('Average Crimes Reported by Month')

# Remove frames
ax.spines[['right', 'top']].set_visible(False)

# Legend
ax.legend_ = None
plt.xticks(rotation=45, ha='right');
```



There is no significant pattern, other than we can see that total reported crimes are highest in May and lowest in December.

We can see if there are any noticeable patterns with regard to types of crime by month

In [31]:

```
# Groupby month and type
crime_month_type = df_filtered.groupby(['Month','Crime type'],as_index = False)
crime_month_type['Average'] = crime_month_type['Year']/2
crime_month_type
```

Out[31]:

	Month	Crime type	Year	Average
0	1	Anti-social & Public Order	5572	2786.0
1	1	Burglary & Robbery	1524	762.0
2	1	Criminal damage and arson	2157	1078.5
3	1	Drugs	750	375.0
4	1	Other crime	429	214.5
...	...	...	...	...
115	12	Possession of weapons	251	125.5
116	12	Shoplifting	1549	774.5
117	12	Theft	2160	1080.0
118	12	Vehicle crime	1550	775.0
119	12	Violence and sexual offences	9583	4791.5

120 rows × 4 columns

In [32]:

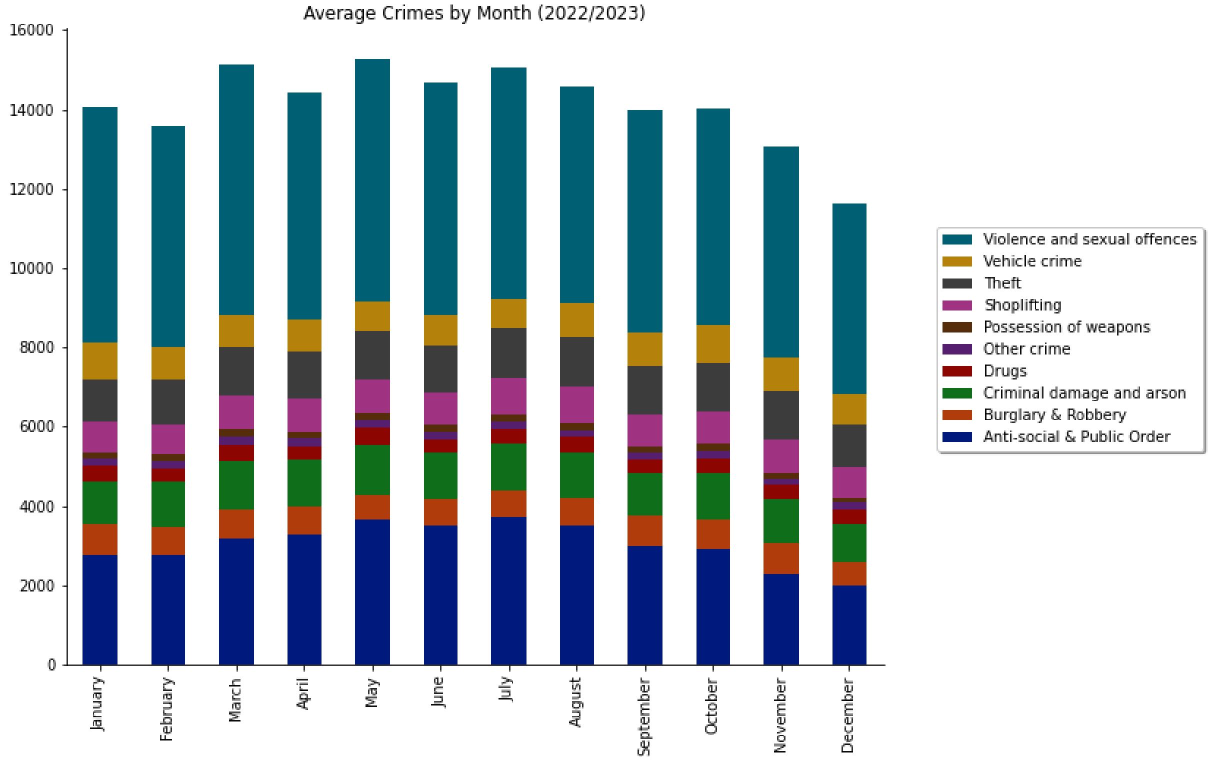
```
# Create pivot table
crime_month_type = crime_month_type.pivot(index = 'Month', columns = 'Crime typ
crime_month_type.index = months
crime_month_type
```

Out[32]:

Crime type	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehicle crime
January	2786.0	762.0	1078.5	375.0	214.5	135.5	773.0	1061.0	928.5
February	2786.0	686.5	1129.5	340.0	202.0	156.5	764.5	1133.0	825.5
March	3168.0	727.0	1239.0	385.0	230.5	178.5	849.0	1222.5	816.5
April	3276.0	698.0	1195.5	337.0	195.5	151.5	877.5	1163.0	821.0
May	3658.0	623.5	1271.0	411.5	195.5	186.5	863.5	1198.5	737.5
June	3514.0	665.5	1158.5	346.0	194.5	167.0	809.5	1188.5	772.5
July	3734.5	675.5	1158.5	365.0	209.0	170.5	929.5	1226.0	747.0
August	3515.0	708.0	1128.0	395.5	167.5	167.5	937.0	1243.0	855.0
September	3001.0	781.0	1039.5	333.5	184.5	174.0	804.5	1193.5	851.5
October	2911.5	742.5	1167.5	381.0	178.0	178.5	827.5	1220.5	960.5
November	2275.0	804.0	1083.5	364.5	173.0	140.5	848.5	1193.5	878.5
December	1982.5	613.0	958.0	358.5	167.5	125.5	774.5	1080.0	775.0

In [33]:

```
# Plot the data
sns.set_palette('dark')

# Plot
fig, ax = plt.subplots(figsize = (10,8))
crime_month_type.plot(ax = ax, kind = 'bar',stacked = True)

# Title
plt.title("Average Crimes by Month (2022/2023)")

# Remove frames
ax.spines[['right', 'top']].set_visible(False)

# Legend
handles, labels = ax.get_legend_handles_labels()
ax.legend(reversed(handles), reversed(labels),loc='upper right', bbox_to_anchor
          ncol=1, fancybox=True, shadow=True);
```



- We can see an increase in anti-social and public order offences reported during the summer months which declines over the year
- Violence and sexual offences also reduce

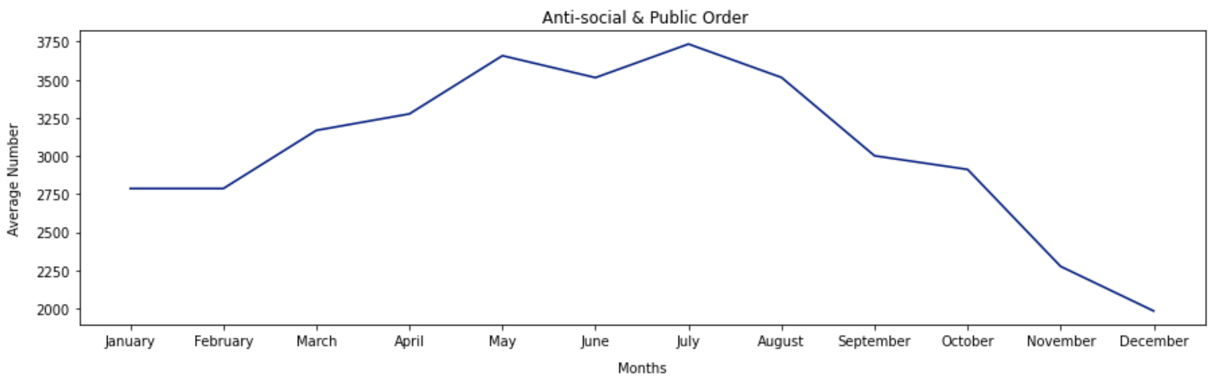
We can see this a little better if we plot each of these crime types separately

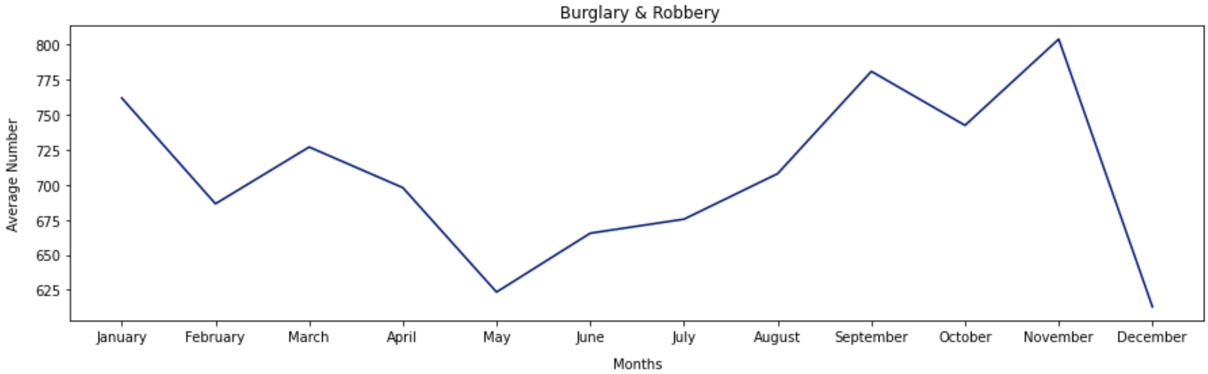
In [34]:

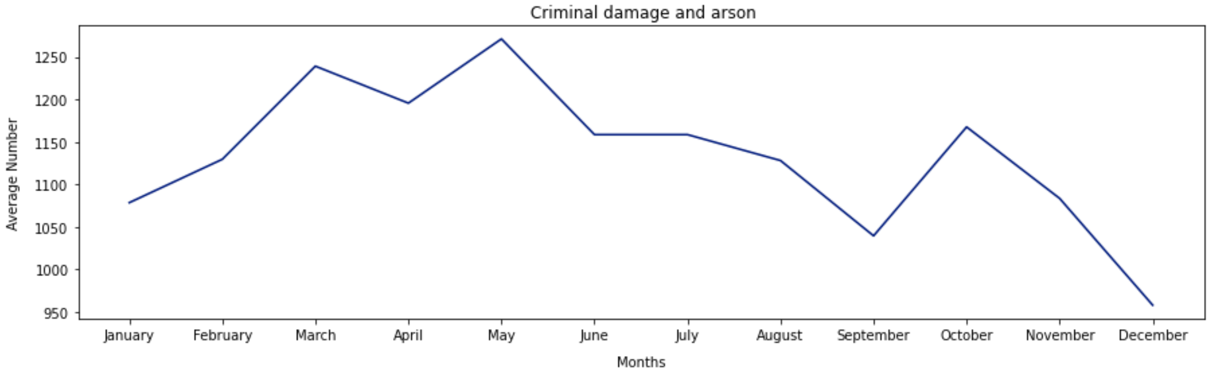
```
def plot_line_charts(df):

    columns = df.columns[:10]  # Select the first 10 columns from the dataframe

    for column in columns:
        plt.figure(figsize = (15,4))
        plt.plot(df.index, df[column])
        plt.title(f" {column}")
        plt.xlabel("Months", labelpad = 10)
        plt.ylabel("Average Number", labelpad = 10)
        plt.show()
```

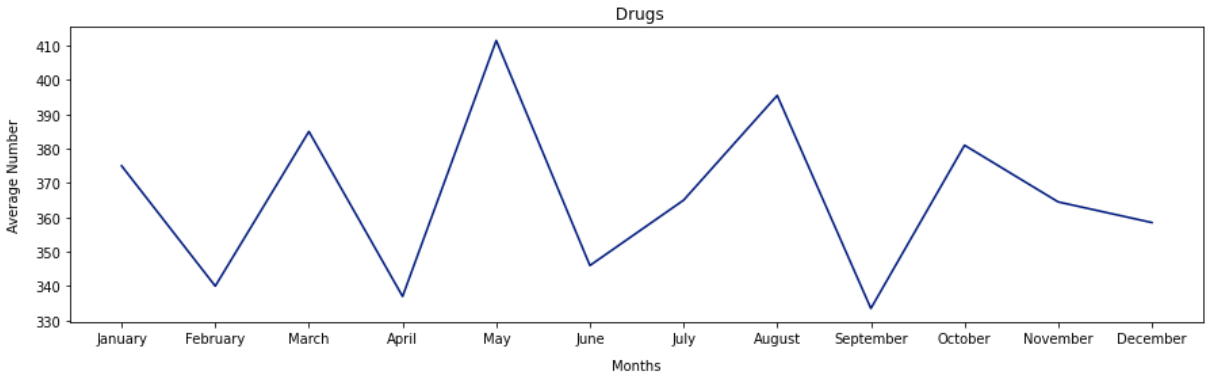
In [35]:

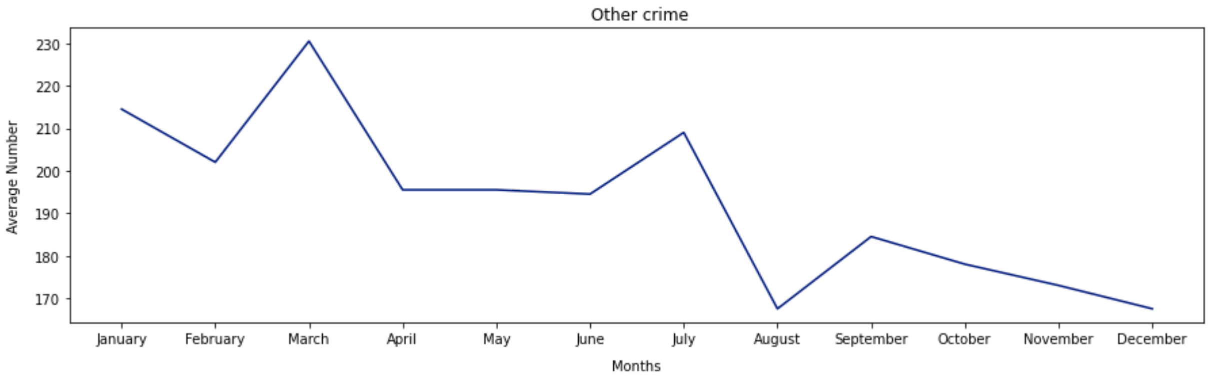
```
plot_line_charts(crime_month_type)
```

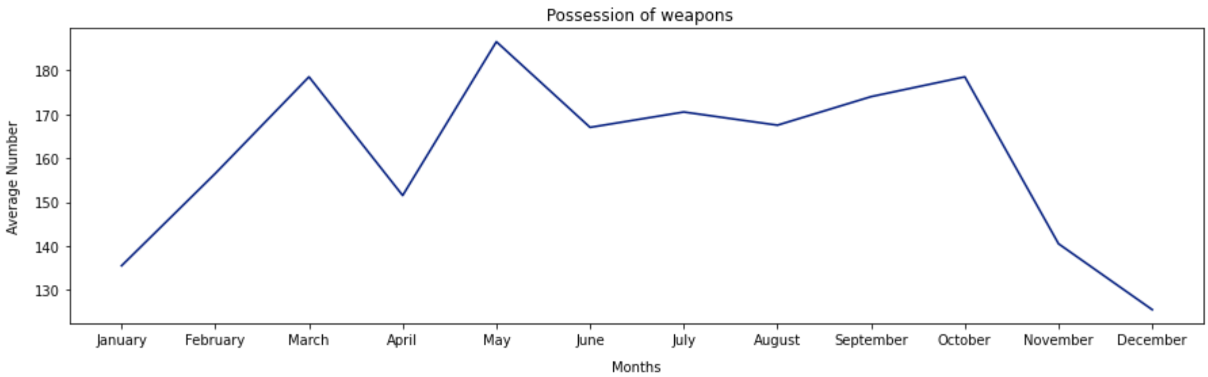


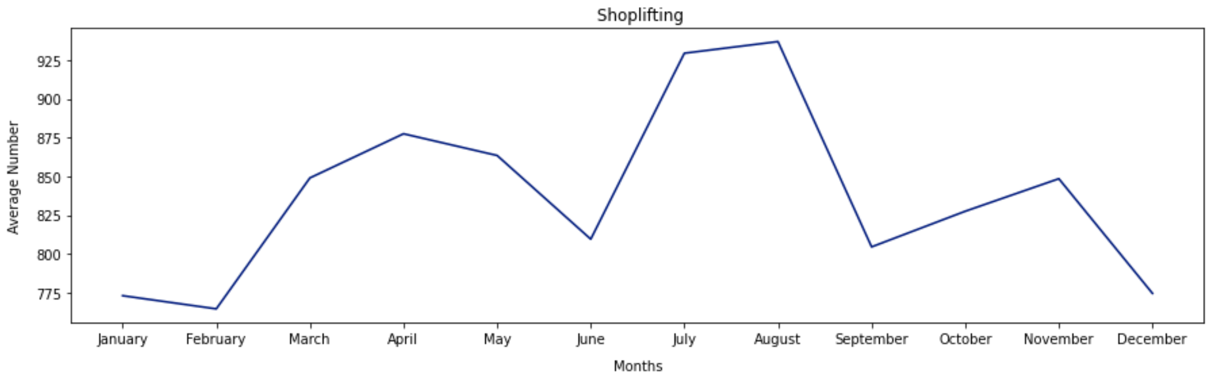

Burglary & Robbery
Average Number
800
775
750
725
700
675
650
625
January
February
March
April
May
June
July
August
September
October
November
December
Months

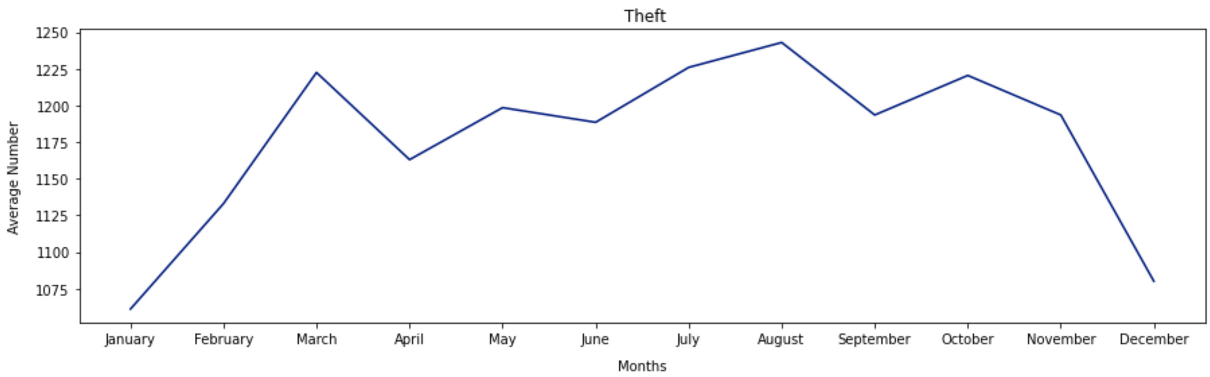

Criminal damage and arson
Average Number
1250
1200
1150
1100
1050
1000
950
January
February
March
April
May
June
July
August
September
October
November
December
Months

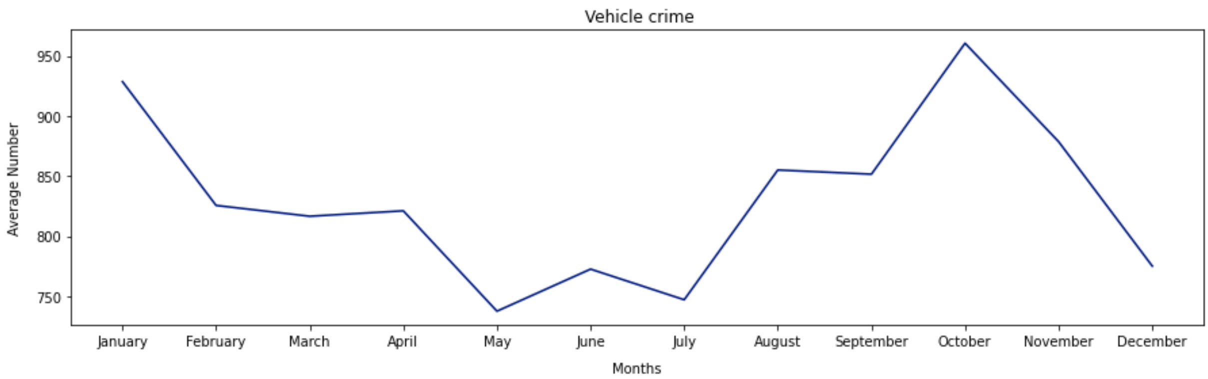

Drugs
Average Number
410
400
390
380
370
360
350
340
330
January
February
March
April
May
June
July
August
September
October
November
December
Months

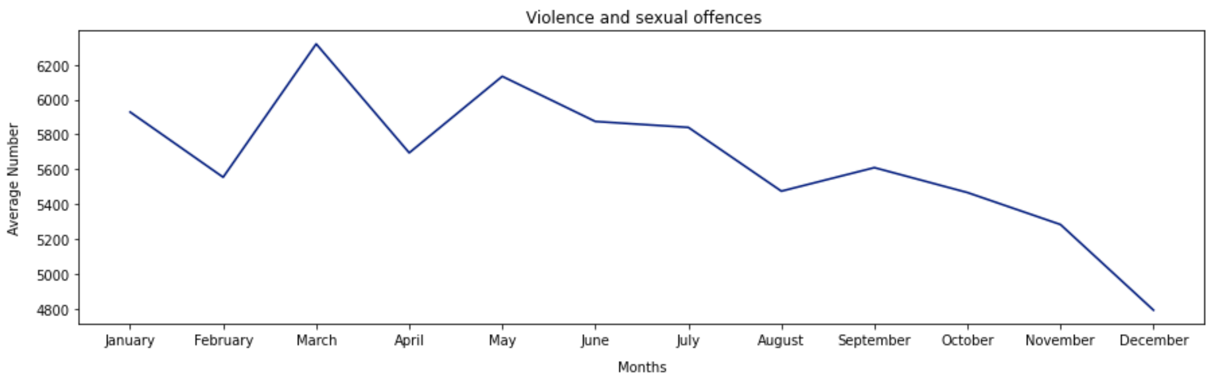

Other crime
Average Number
230
220
210
200
190
180
170
January
February
March
April
May
June
July
August
September
October
November
December
Months


Possession of weapons
Average Number
180
170
160
150
140
130
January
February
March
April
May
June
July
August
September
October
November
December
Months









Pattern of crimes by month:

- Anti-social and public order increases over the summer and then decreases into the winter. This might align with protests and riots occurring over the better summer weather, increased drinking out of the home over the summer etc.
- Burglary & Robbery hits a low point in May and then increases gradually over the rest of the year to a peak in November prior to the Christmas period
- Criminal damage and arson is highest in May as the weather increases with another peak in October. These might coincide with holiday periods.
- Drugs crime has a distinct cyclical pattern peaking in March, May, August and October, possibly in line with school holidays

- Other crime - no comments
- Possession of weapons has similar peaks as drug crime but without the dips, again indicating possible association with drug crime
- Shoplifting has peaks in April, over the summer and a smaller increase in November. Some of this might be associated with school holidays at Easter, Summer and prior to Christmas.
- Theft increases in January through to March and then remains high over the summer and autumn only dipping in December.
- Vehicle crime is at a peak in October and much lower over the summer, which might be related to break-ins to steal items bought for Christmas and left in the car
- Violence and sexual offences appear to peak in March and then decline over the rest of the year.

Crimes by district

To analyse the crimes by district, we can filter by the LSOA codes we used earlier.

In [36]:

```
# Add a district column
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Basingstoke')), 'Distri
df_filtered.loc[(df_filtered['LSOA name'].str.contains('East Hamp')), 'District
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Eastleigh')), 'District
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Fareham')), 'District']
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Gosport')), 'District']
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Havant')), 'District']
df_filtered.loc[(df_filtered['LSOA name'].str.contains('New Forest')), 'Distric
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Portsmouth')), 'Distric
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Rushmoor')), 'District'
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Southampton')), 'Distri
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Test Valley')), 'Distri
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Winchester')), 'Distric
df_filtered.loc[(df_filtered['LSOA name'].str.contains('Hart ')), 'District'] =
```

In [37]:

```
df_filtered.head()
```

Out[37]:

	Longitude	Latitude	Location	LSOA code	LSOA name	Crime type	Last outcome category	Year
151109	-1.144834	51.353800	On or near Stanfield	E01022553	Basingstoke and Deane 001A	Theft	Unable to prosecute suspect	2022
151110	-1.151854	51.357016	On or near Supermarket	E01022554	Basingstoke and Deane 001B	Anti-social & Public Order	Local resolution	2022
151111	-1.153329	51.357269	On or near The Burrows	E01022554	Basingstoke and Deane 001B	Violence and sexual offences	Unable to prosecute suspect	2022
151112	-1.141741	51.354829	On or near The Parade	E01022555	Basingstoke and Deane	Anti-social &	NaN	2022

	Longitude	Latitude	Location	LSOA code	LSOA name	Crime type	Last outcome category	Year
					001C	Public Order		
151113	-1.140079	51.350798	On or near Maple Grove	E01022555	Basingstoke and Deane 001C	Anti-social & Public Order	NaN	2022

In [38]:

```
crime_district = df_filtered.groupby(['District','Crime type'],as_index = False
crime_district['Average'] = crime_district['Month']/2
crime_district
```

Out[38]:

	District	Crime type	Month	Average
0	Basingstoke	Anti-social & Public Order	6213	3106.5
1	Basingstoke	Burglary & Robbery	1391	695.5
2	Basingstoke	Criminal damage and arson	2332	1166.0
3	Basingstoke	Drugs	678	339.0
4	Basingstoke	Other crime	445	222.5
...	...	...	...	...
125	Winchester	Possession of weapons	156	78.0
126	Winchester	Shoplifting	1038	519.0
127	Winchester	Theft	1678	839.0
128	Winchester	Vehicle crime	1238	619.0
129	Winchester	Violence and sexual offences	6835	3417.5

130 rows × 4 columns

In [39]:

```
crime_district_pivot = crime_district.pivot(index = 'District',columns = 'Crime
crime_district_pivot = crime_district_pivot.sort_index()
crime_district_pivot['Total'] = crime_district_pivot.iloc[:, 0:].sum(axis=1)
crime_district_pivot
```

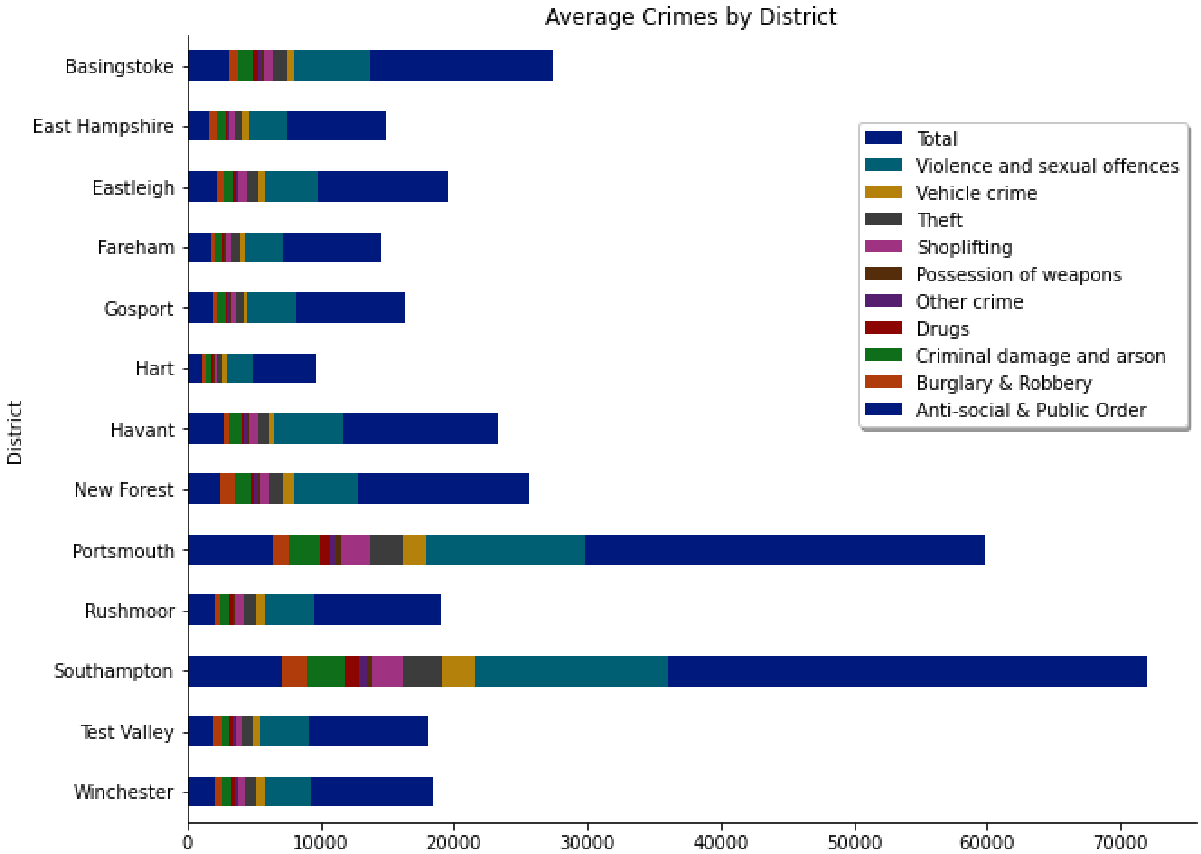
Out[39]:

Crime type	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
District									
Basingstoke	3106.5	695.5	1166.0	339.0	222.5	159.0	690.5	1136.5	565
East Hampshire	1693.0	491.0	647.0	170.5	103.5	60.5	321.0	664.5	497

Crime type	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
District									
Eastleigh	2201.0	519.5	745.5	173.0	143.5	87.0	596.5	785.0	619
Fareham	1720.5	292.5	542.0	127.5	97.5	63.0	485.5	601.0	386
Gosport	1936.5	267.5	690.5	172.5	111.5	90.0	409.5	604.5	279
Hart	1134.0	264.0	402.0	95.5	70.5	44.5	142.5	484.0	338
Havant	2717.5	386.0	927.0	263.0	172.5	128.0	671.5	826.0	436
New Forest	2531.0	987.0	1271.5	301.0	173.0	123.5	677.5	1159.5	795
Portsmouth	6380.5	1186.5	2337.5	862.0	343.5	417.5	2183.5	2408.5	1740
Rushmoor	2060.5	374.0	687.0	237.5	120.0	108.5	694.5	832.5	712
Southampton	7123.5	1908.5	2839.0	1100.0	444.0	486.5	2191.5	3027.0	2452
Test Valley	1927.0	610.5	660.0	241.0	137.5	86.0	475.5	755.0	529
Winchester	2076.0	504.0	692.0	310.0	172.5	78.0	519.0	839.0	619

In [40]:

```
# Plot the data
fig, ax = plt.subplots(figsize = (10,8))
crime_district_pivot.plot(ax = ax, kind = 'barh', stacked = True)

# Title
plt.title("Average Crimes by District")

# Remove frames
ax.spines[['right', 'top']].set_visible(False)

ax.invert_yaxis()

# Legend
handles, labels = ax.get_legend_handles_labels()
ax.legend(reversed(handles), reversed(labels),loc='upper right', bbox_to_anchor
          ncol=1, fancybox=True, shadow=True);
```



We can see that the largest offences are reported in the two largest towns/cities in Hampshire, Portsmouth and Southampton with violence and sexual offences being the largest category. The lowest number of crimes is reported in Hart, a rural district.

In [41]:

```
# Add total crimes by district column
crime_district_pivot['Total']=crime_district_pivot.sum(axis = 1)

# Add the population from the 2021 census for each district

crime_district_pivot.insert(11, "Pop", [185200,125700,136400,114500,
                                        81900,99400,124200,175800,
                                        208100,99800,249000,130500,127500],True)

# Add crimes per head
crime_district_pivot['Crimes per head'] = crime_district_pivot['Total']/crime_d
```

In [42]:

```
crime_district_pivot.sort_values(by = 'Crimes per head',ascending = False)
```

Out[42]:

Crime type	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
District									
Southampton	7123.5	1908.5	2839.0	1100.0	444.0	486.5	2191.5	3027.0	2452
Portsmouth	6380.5	1186.5	2337.5	862.0	343.5	417.5	2183.5	2408.5	1740
Gosport	1936.5	267.5	690.5	172.5	111.5	90.0	409.5	604.5	279

Crime type	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
District									
Rushmoor	2060.5	374.0	687.0	237.5	120.0	108.5	694.5	832.5	712
Havant	2717.5	386.0	927.0	263.0	172.5	128.0	671.5	826.0	436
Basingstoke	3106.5	695.5	1166.0	339.0	222.5	159.0	690.5	1136.5	565
New Forest	2531.0	987.0	1271.5	301.0	173.0	123.5	677.5	1159.5	795
Winchester	2076.0	504.0	692.0	310.0	172.5	78.0	519.0	839.0	619
Eastleigh	2201.0	519.5	745.5	173.0	143.5	87.0	596.5	785.0	619
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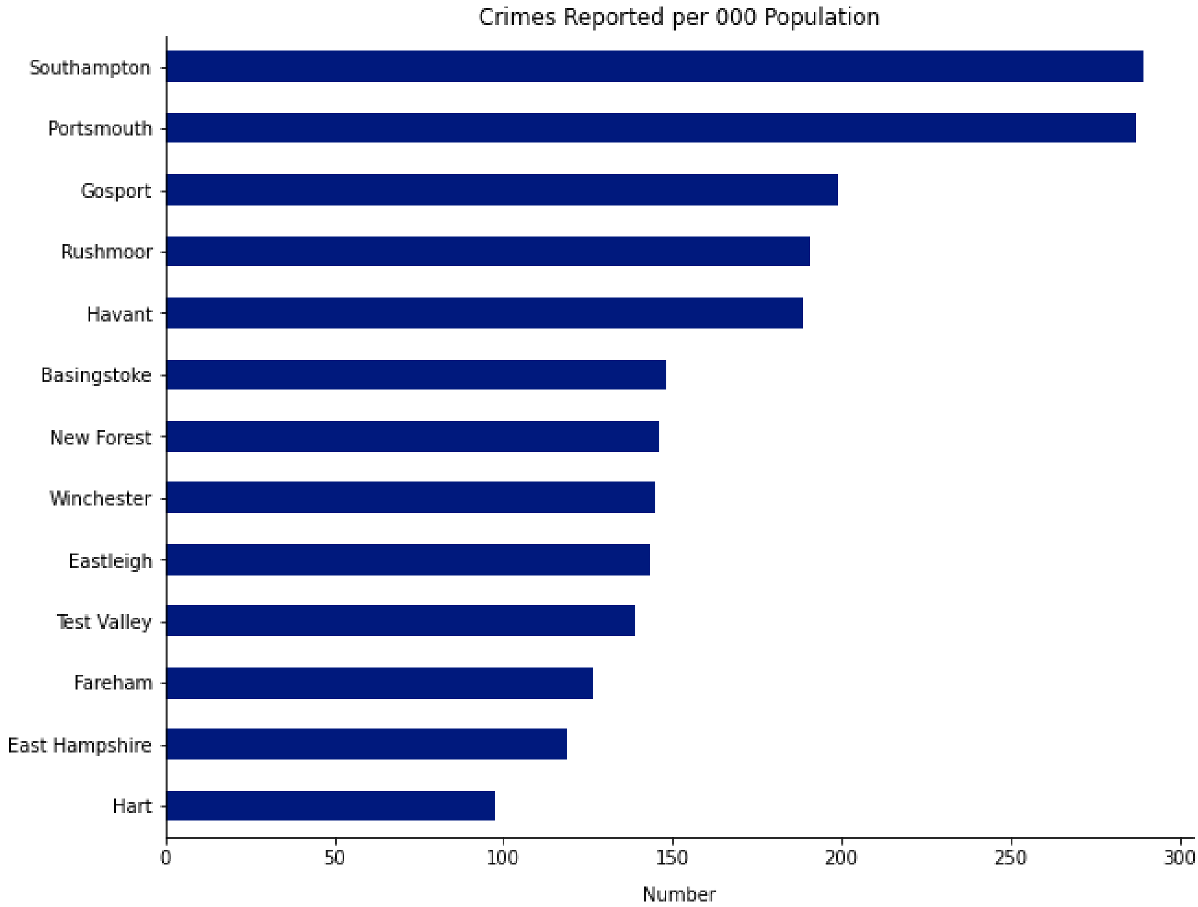
Fareham	1720.5	292.5	542.0	127.5	97.5	63.0	485.5	601.0	386
East Hampshire	1693.0	491.0	647.0	170.5	103.5	60.5	321.0	664.5	497
Hart	1134.0	264.0	402.0	95.5	70.5	44.5	142.5	484.0	338

In [43]:

```
# Plot the data
fig, ax = plt.subplots(figsize = (10,8))
crime_district_pivot['Crimes per head'].sort_values(ascending = False).plot(ax 

ax.invert_yaxis()
plt.title('Crimes Reported per 000 Population')
plt.xlabel('Number', labelpad = 10)
plt.ylabel("")

# Remove frames
ax.spines[['right', 'top']].set_visible(False)
```



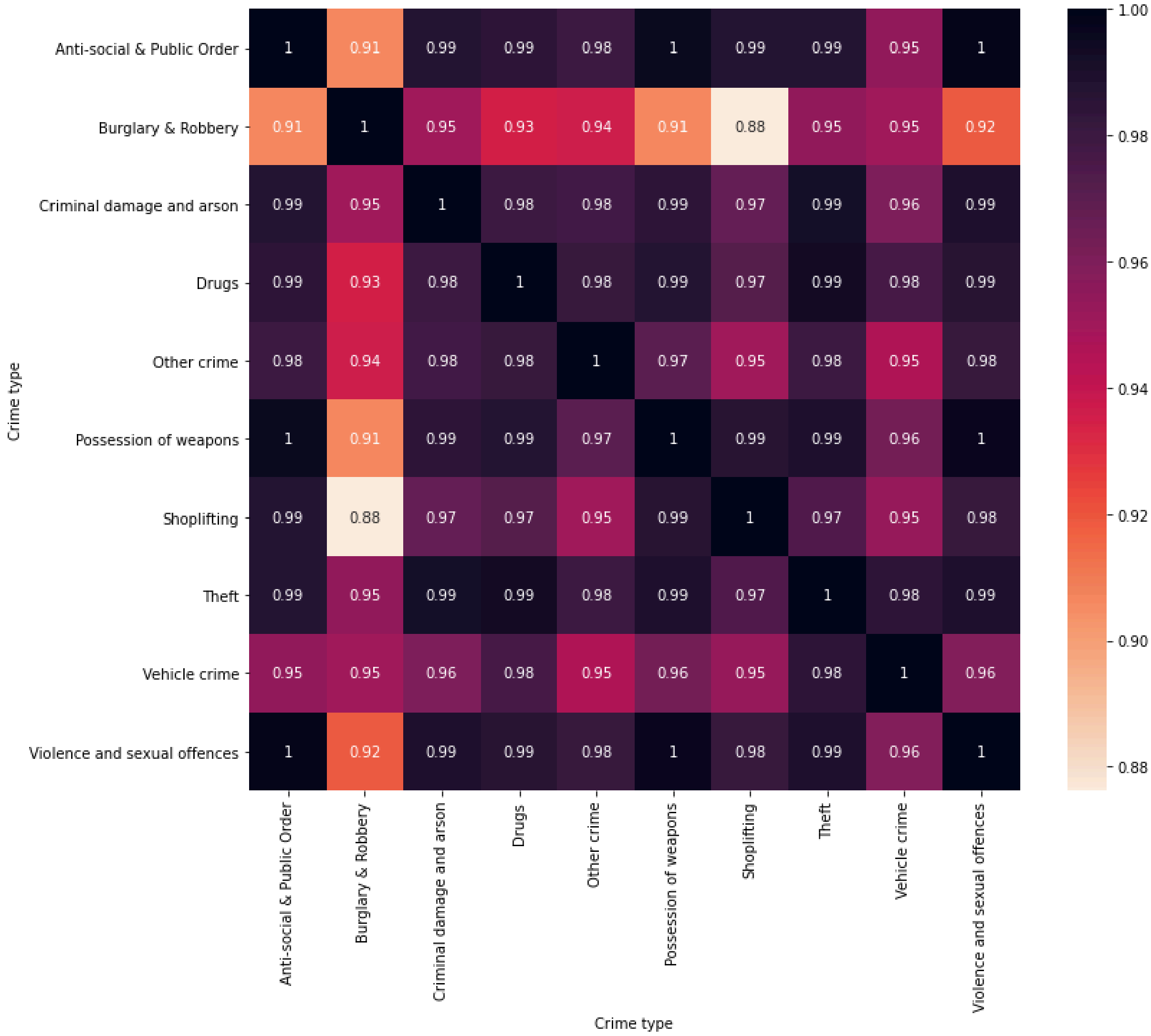
- On average Southampton has just over 36000 crimes reported per year. When expressed per head of population, this equates to 140 crimes per 000 population of which 40% is violent and sexual offences.
- For Portsmouth, the picture is similar with a slightly lower number of crimes with a smaller population resulting in 140 reported crimes per 000 population.
- The lowest reported crimes per head is in the district of Hart at just under 50 crimes per 000 population
- It appears that the two largest connurbations also have the highest crime levels per head

Relationship between crimes

In [44]:

```
crime_corr = crime_district_pivot.iloc[:,0:10].corr()

# Lets look at a heatmap
cmap = sns.cm.rocket_r
fig, ax = plt.subplots(figsize = (12,10))
sns.heatmap(crime_corr, annot = True, cmap = cmap);
```



There is pretty strong correlation between different types of crime being reported in a district. This is what we might expect. For example drugs offences are highly positively correlated with theft, violence, possession of weapons and anti-social behaviour. Shoplifting and burglary are less highly correlated.

What are the hotspots for particular crimes?

Look at the top three districts for each type of crime reported. We might expect Southampton, Portsmouth and Basingstoke to be the highest on all crimes but there may be some differences in the results.

In [49]:

```
# Sort the table by each crime in descending order and take the top 3
for i in crime_district_pivot.columns[0:10]:
    r = crime_district_pivot.sort_values(by = i,ascending = False).head(10)
    display(r)
```

Crime type	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
District									
Southampton	7123.5	1908.5	2839.0	1100.0	444.0	486.5	2191.5	3027.0	2452
Portsmouth	6380.5	1186.5	2337.5	862.0	343.5	417.5	2183.5	2408.5	1740
Basingstoke	3106.5	695.5	1166.0	339.0	222.5	159.0	690.5	1136.5	565
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Gosport	1936.5	267.5	690.5	172.5	111.5	90.0	409.5	604.5	279

Crime type	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
District									
Southampton	7123.5	1908.5	2839.0	1100.0	444.0	486.5	2191.5	3027.0	2452
Portsmouth	6380.5	1186.5	2337.5	862.0	343.5	417.5	2183.5	2408.5	1740
Basingstoke	3106.5	695.5	1166.0	339.0	222.5	159.0	690.5	1136.5	565
Havant	2717.5	386.0	927.0	263.0	172.5	128.0	671.5	826.0	436
New Forest	2531.0	987.0	1271.5	301.0	173.0	123.5	677.5	1159.5	795
Rushmoor	2060.5	374.0	687.0	237.5	120.0	108.5	694.5	832.5	712
Gosport	1936.5	267.5	690.5	172.5	111.5	90.0	409.5	604.5	279
Eastleigh	2201.0	519.5	745.5	173.0	143.5	87.0	596.5	785.0	619
Test Valley	1927.0	610.5	660.0	241.0	137.5	86.0	475.5	755.0	529
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Fareham	1720.5	292.5	542.0	127.5	97.5	63.0	485.5	601.0	386
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East Hampshire	1693.0	491.0	647.0	170.5	103.5	60.5	321.0	664.5	497

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Winchester	2076.0	504.0	692.0	310.0	172.5	78.0	519.0	839.0	619

Crime categories where other districts feature

- Burglary & Robbery/Criminal damage and arson/Theft/Vehicle crime - New Forest 3rd place
- Shoplifting - Rushmoor 3rd place

The New Forest is an area that receives a lot of visitors and there are a lot of expensive homes in this district too. This could explain it being a hotspot for these types of crimes

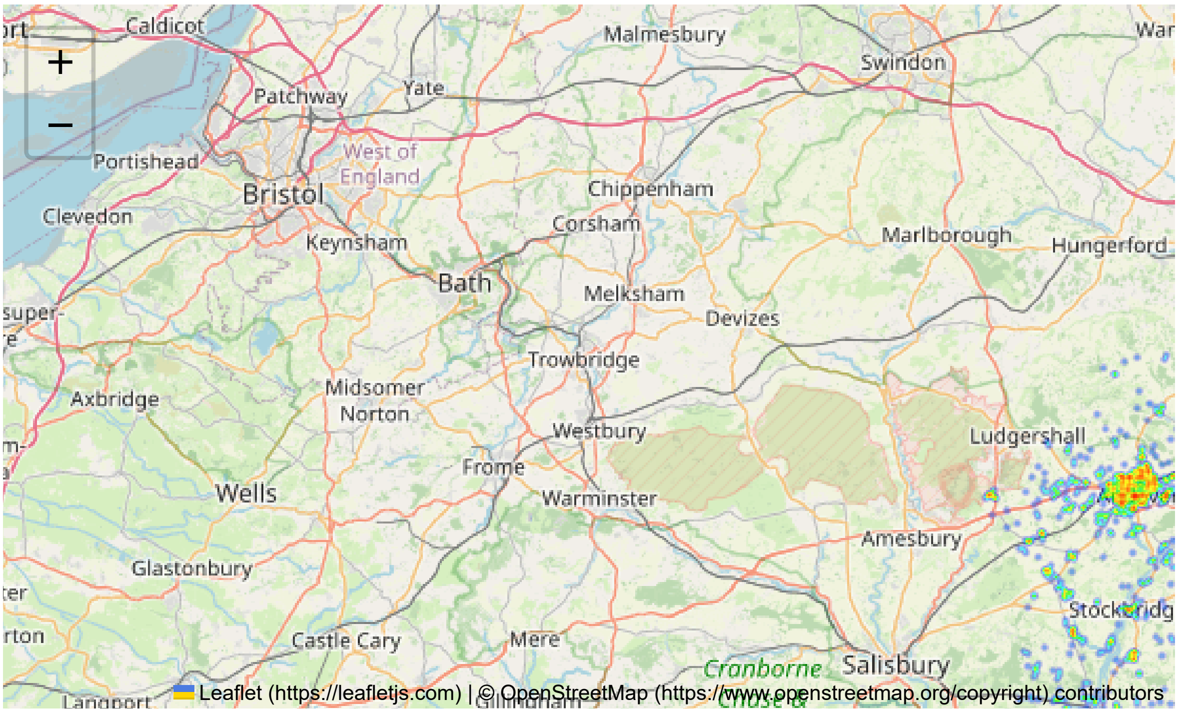
Rushmoor encompasses the towns of Farnborough and Aldershot, both military areas but it is not clear why it appears in third place for shoplifting

Lets plot this on a map. We are using the full dataframe here with latitude and longitude and crimes cover the two year period of 2022 and 2023.

In [46]:

```
# Map these crimes on a map of England and Wales (2022 and 2023)

lat = df_filtered['Latitude'].to_list()
long = df_filtered['Longitude'].to_list()

crime_map = folium.Map([50.9, -1.08], zoom_start=9)

heatmap = plugins.HeatMap(list(zip(lat,long)),radius = 2, blur = 1)
crime_map.add_child(heatmap)
```

Out[46]:



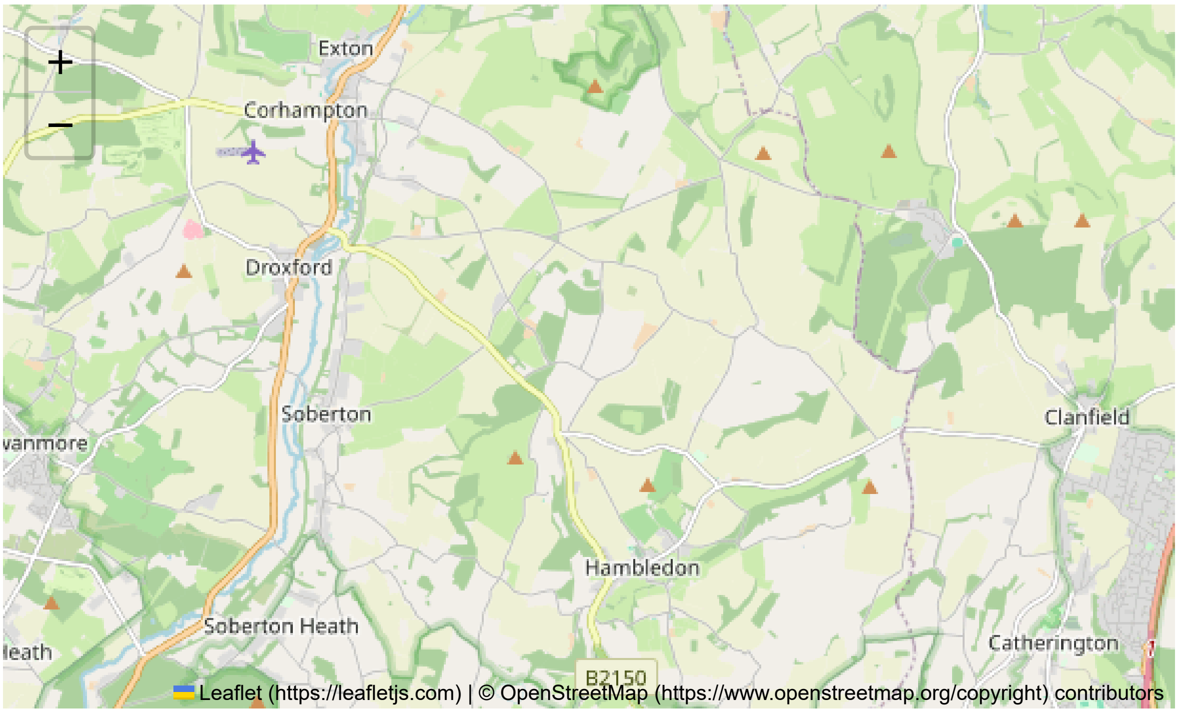
We can clearly see the hotspots in Hampshire on the map and these are clustered around the major connurbations as we might expect

In [50]:

```
# Lets have a closer look at Havant (2022 and 2023)

hav = df_filtered[df_filtered['District']=='Havant']

# Map these crimes on a map of England and Wales

lat = hav['Latitude'].to_list()
long = hav['Longitude'].to_list()
```

```
crime_map = folium.Map([50.9, -0.95], zoom_start=12)

heatmap = plugins.HeatMap(list(zip(lat,long)),radius = 3, blur = 1)
crime_map.add_child(heatmap)
```

Out[50]:



There are some hotspot areas in the Havant district that we can narrow down to locations

In [51]:

```
hav.groupby(['LSOA code'], as_index = False)['Year'].count().sort_values(by = ''
```

Out[51]:

	LSOA code	Year
71	E01022973	1307
51	E01022953	1172
6	E01022905	934
4	E01022903	772
15	E01022915	718

There are a couple of locations of interest

In [52]:

```
# Look at the first location -crimes over the two year period
hav[hav['LSOA code']=='E01022973'].groupby('Crime type',as_index = False)['Year
```

Out[52]:

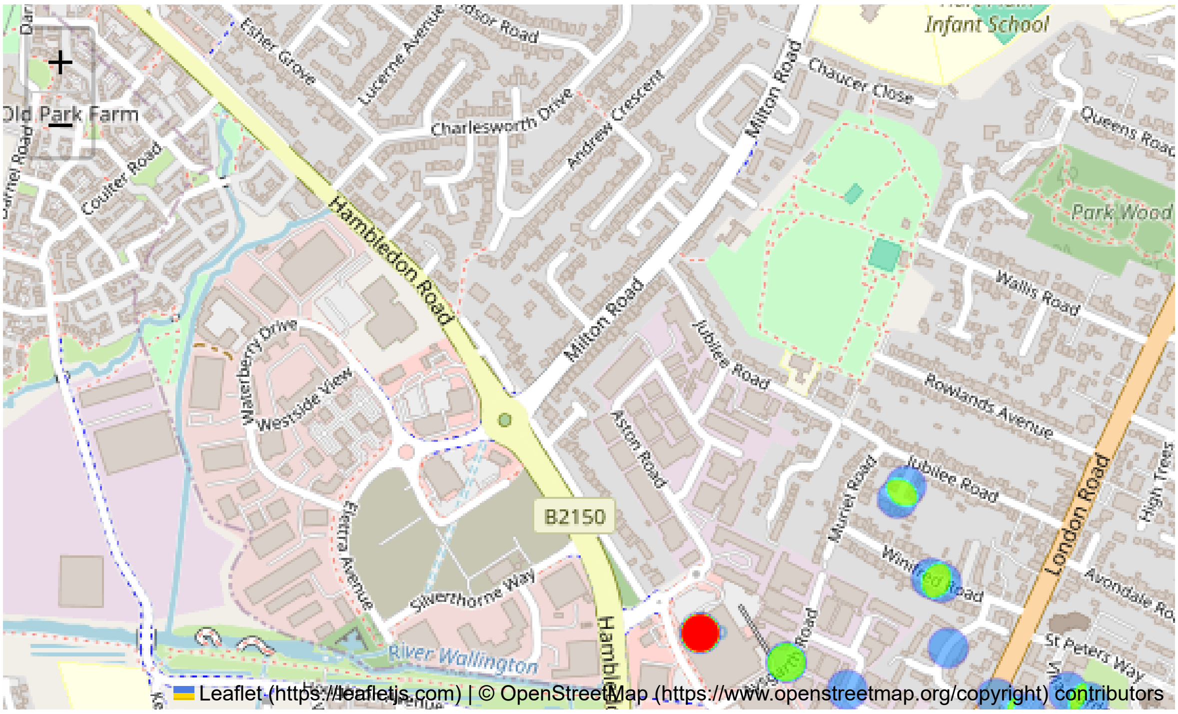
	Crime type	Year
9	Violence and sexual offences	363
0	Anti-social & Public Order	351
6	Shoplifting	306
7	Theft	111
2	Criminal damage and arson	68

	Crime type	Year
1	Burglary & Robbery	50
5	Possession of weapons	22
3	Drugs	20
8	Vehicle crime	14
4	Other crime	2

We can see that most of these involve violence and sexual offences, followed by anti-social and public order and shoplifting. We could try to narrow this down a little more.

In [55]:
```
# Lets have a closer look at Havant (2022 and 2023)

E01022973 = hav[hav['LSOA code']=='E01022973']

# Map these crimes on a map of England and Wales

lat = E01022973['Latitude'].to_list()
long = E01022973['Longitude'].to_list()

crime_map = folium.Map([50.88, -1.02], zoom_start=15)

heatmap = plugins.HeatMap(list(zip(lat,long)),radius = 10, blur = 1)
crime_map.add_child(heatmap)
```

Out[55]:



This LSOA is actually in Waterlooville, a nearby town to Havant but in the Havant and Waterlooville District

In [56]:
```
# Look at the first Location -crimes over the two year period
E01022973.groupby('Location',as_index = False)['Year'].count().sort_values(by =
```

Out[56]:

	Location	Year
0	On or near	281
25	On or near Supermarket	167
26	On or near Swiss Road	121
2	On or near Aysgarth Road	114
20	On or near Portland Road	105

This first line doesn't provide much information, although we can see a couple of locations of interest which are around the central town shopping area

In [57]:

```
# Look at the other LSOA
hav[hav['LSOA code']=='E01022953'].groupby('Crime type',as_index = False)['Year
```

Out[57]:

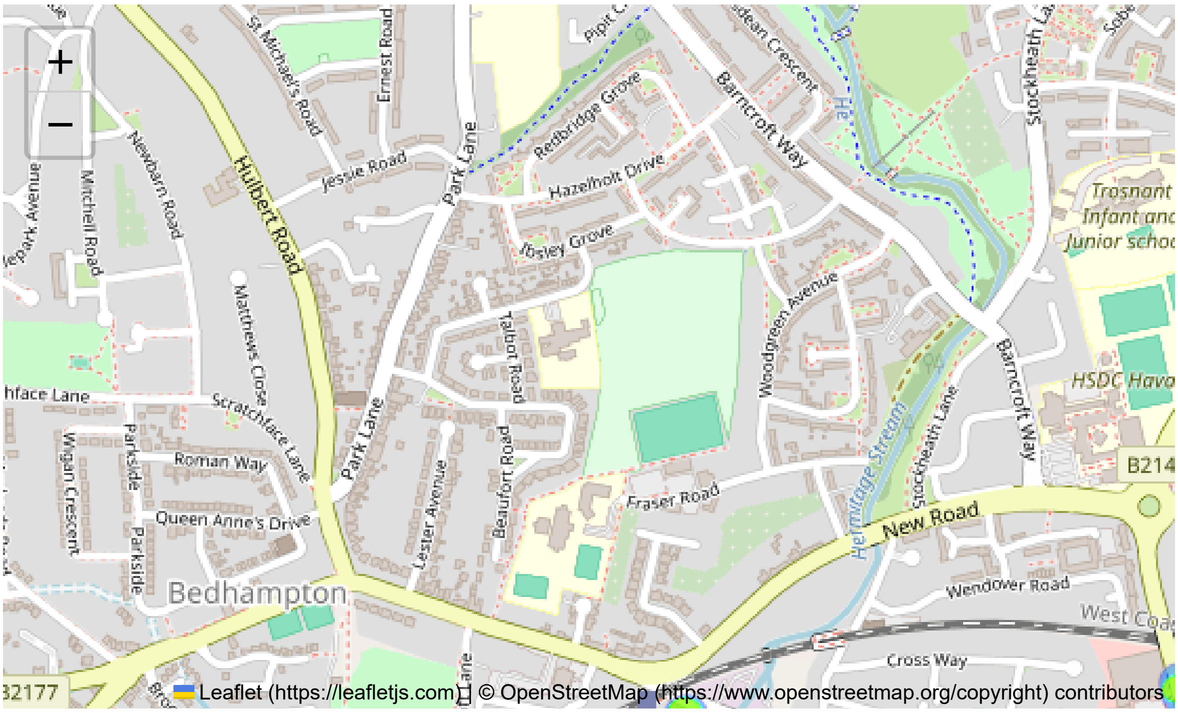
	Crime type	Year
0	Anti-social & Public Order	338
9	Violence and sexual offences	321
6	Shoplifting	222
7	Theft	115
2	Criminal damage and arson	69
1	Burglary & Robbery	40
8	Vehicle crime	30
3	Drugs	22
5	Possession of weapons	12
4	Other crime	3

In this area, anti-social and public order offences are the top reported crime. Again, violence and shoplifting are also top reported crimes for this LSOA.

In [58]:

```
# Lets have a closer look at Havant (2022 and 2023)

E01022953 = hav[hav['LSOA code']=='E01022953']

# Map these crimes on a map of England and Wales

lat = E01022953['Latitude'].to_list()
long = E01022953['Longitude'].to_list()

crime_map = folium.Map([50.8518, -0.98], zoom_start=15)

heatmap = plugins.HeatMap(list(zip(lat,long)),radius = 10, blur = 1)
crime_map.add_child(heatmap)
```

Out[58]:



In [59]:

```
# Look at the first location -crimes over the two year period
E01022953.groupby('Location',as_index = False)['Year'].count().sort_values(by =
```

Out[59]:

	Location	Year
0	On or near	366
31	On or near Shopping Area	70
5	On or near Bulbeck Road	68
18	On or near Market Parade	67
6	On or near Bus/Coach Station	65

As before, there is not much information regarding the location name but we can see from the map the hotpspot areas which are again focussed primarily on the shopping centre areas

Economic Indicators

It might be interesting to have a look at some other economic indicators such as unemployment rates, median incomes or education to try to build up a picture by district and see if there are any obvious links between crime rate and other factors. From this we might be able to build up a model.

We will look at:

- Unemployment figures
- Median household income
- Population density

In [61]:

```
# Read in some other indicators
eco = pd.read_csv(r'C:\Users\imoge\AllMLProjects\Data\EconomicHants.csv')
```

```
eco
```

Out[61]:

	Unnamed: 0	med_salary	unemp_rate	Land_area
0	Basingstoke	39000.0	3.3	633.80
1	East Hampshire	33000.0	3.1	514.40
2	Eastleigh	34400.0	2.3	80.00
3	Fareham	35800.0	2.4	74.20
4	Gosport	32100.0	3.4	25.29
5	Hart	39300.0	3.0	215.30
6	Havant	32900.0	4.0	55.30
7	New Forest	34600.0	2.9	753.20
8	Portsmouth	35200.0	3.8	40.25
9	Rushmoor	38400.0	3.0	39.00
10	Southampton	35700.0	4.6	72.80
11	Test Valley	35100.0	2.3	627.60
12	Winchester	37100.0	3.0	660.97
13	NaN	NaN	NaN	NaN
14	NaN	NaN	NaN	NaN
15	NaN	NaN	NaN	NaN

In [62]:

```
# Drop the last few rows
eco = eco.iloc[0:13,:]

# Rename the first column
eco.rename(columns = {'Unnamed: 0':'District Name'}, inplace = True)
```

In [63]:

```
# Check the datatypes
eco.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13 entries, 0 to 12
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   District Name  13 non-null     object
 1   med_salary     13 non-null     float64
 2   unemp_rate     13 non-null     float64
 3   Land_area      13 non-null     float64
dtypes: float64(3), object(1)
memory usage: 544.0+ bytes
```

In [64]:

```
eco
```

Out[64]:

	District Name	med_salary	unemp_rate	Land_area
0	Basingstoke	39000.0	3.3	633.80

	District Name	med_salary	unemp_rate	Land_area
1	East Hampshire	33000.0	3.1	514.40
2	Eastleigh	34400.0	2.3	80.00
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10	Southampton	35700.0	4.6	72.80
11	Test Valley	35100.0	2.3	627.60
12	Winchester	37100.0	3.0	660.97

In [135…

```
# Merge with the economic indicators
crime_district_all = crime_district_pivot.merge(eco, left_on = 'District', righ
```

In [136…

```
# Add column for population density
crime_district_all['Pop_density']= crime_district_all['Pop']/crime_district_all
```

In [137…

```
# Set the names of districts as index
crime_district_all.set_index('District Name', inplace = True)
```

In [138…

```
crime_district_all.head()
```

Out[138…

District Name	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehicle crime
Basingstoke	3106.5	695.5	1166.0	339.0	222.5	159.0	690.5	1136.5	565.0
East Hampshire	1693.0	491.0	647.0	170.5	103.5	60.5	321.0	664.5	497.5
Eastleigh	2201.0	519.5	745.5	173.0	143.5	87.0	596.5	785.0	619.5
Fareham	1720.5	292.5	542.0	127.5	97.5	63.0	485.5	601.0	386.0
Gosport	1936.5	267.5	690.5	172.5	111.5	90.0	409.5	604.5	279.0

In [139…

```
# Drop columns not wanted
crime_district_all.drop(columns = ['Land_area','Pop'],axis = 1, inplace = True)
```

In [140…

```
# Check head
crime_district_all
```

Out[140…

District Name	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
Basingstoke	3106.5	695.5	1166.0	339.0	222.5	159.0	690.5	1136.5	565
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Gosport	1936.5	267.5	690.5	172.5	111.5	90.0	409.5	604.5	279
Hart	1134.0	264.0	402.0	95.5	70.5	44.5	142.5	484.0	338
Havant	2717.5	386.0	927.0	263.0	172.5	128.0	671.5	826.0	436
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Test Valley	1927.0	610.5	660.0	241.0	137.5	86.0	475.5	755.0	529
Winchester	2076.0	504.0	692.0	310.0	172.5	78.0	519.0	839.0	619

Lets try clustering on this data

In [157…

```
# Create new dataframe, drop the total column and shuffle
df_cluster = crime_district_all.drop(columns = ['Total'],axis = 1).sample(frac 
df_cluster
```

Out[157…

District Name	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
New Forest	2531.0	987.0	1271.5	301.0	173.0	123.5	677.5	1159.5	795

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Eastleigh	2201.0	519.5	745.5	173.0	143.5	87.0	596.5	785.0	619

In [158…

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

In [159…

```
object = StandardScaler()
standard = object.fit_transform(df_cluster)
standard
```

Out[159…

```
array([[-0.16288866,  0.74422602,  0.32014892, -0.12866817, -0.04765897,
        -0.18828374, -0.15462975,  0.10018044,  0.04774922, -0.12037444,
        -0.43377056, -0.44191034, -0.4031652 , -0.92527266],
       [-0.64190312, -0.36033593, -0.56920232, -0.58390393, -0.73114919,
        -0.66057895, -0.72747675, -0.57805329, -0.44884266, -0.67253282,
        -0.90458043, -1.16001465, -0.0948624 , -0.91814009],
       [-0.50271455, -0.85805689, -0.50725392, -0.57692714, -0.65247406,
        -0.43942485, -0.58526929, -0.66026344, -0.81295449, -0.46278525,
         0.48768666, -1.56394832,  0.3675918 ,  1.03066435],
       [-0.50814491, -0.09421667, -0.55068901, -0.33797197, -0.39677988,
        -0.46941184, -0.47921627, -0.45405298, -0.39635057, -0.44518991,
        -0.55636741, -0.21750275, -1.32807362, -0.94185022],
       [-0.96143664, -0.86585118, -0.91810713, -0.84553368, -1.05568411,
        -0.78052694, -1.01430196, -0.82536882, -0.71463597, -0.9350664 ,
        -1.27359047,  1.66752106, -0.2490138 , -0.77668983],
       [ 2.46225921,  2.7963507 ,  2.55242766,  2.65856075,  2.61746115,
         2.53303628,  2.27816226,  2.65897134,  2.80816684,  2.57827522,
         2.07257258,  0.05178637,  2.21740863,  1.1490579 ],
       [-0.05628222, -0.59416457, -0.17045397, -0.26122724, -0.05257617,
```

```
 -0.15454837, -0.16427094, -0.35677097, -0.55132723, -0.01661782,
  0.30863662, -1.20489617,  1.29250021,  0.38465646],
[-0.43183413, -0.62088784, -0.51223827, -0.35018135, -0.56888173,
 -0.30073498, -0.12731307, -0.34786487, -0.09139649, -0.42801352,
  0.35196045,  1.26358738, -0.2490138 ,  0.58841234],
[ 2.0375483 ,  1.18850044,  1.83824087,  1.82832235,  1.62910479,
  2.01576057,  2.26530735,  1.81152172,  1.62251207,  1.89708438,
  2.03357398, -0.17262123,  0.98419741,  2.28801804],
[-0.62618367, -0.8023834 , -0.71873296, -0.73390499, -0.79015554,
 -0.64183708, -0.46314763, -0.66505903, -0.63464801, -0.64195045,
 -0.76983071,  0.09666789, -1.17392221, -0.0727904 ],
[ 0.16607652,  0.09507318,  0.16990624,  0.0038909 ,  0.43914341,
  0.07785086, -0.13374052,  0.06866655, -0.3363596 ,  0.11953656,
 -0.38953773,  1.5328765 ,  0.2134404 , -0.88699943],
[-0.42297408, -0.33138572, -0.50511777, -0.0972726 , -0.05257617,
 -0.52938584, -0.40931769, -0.33895877, -0.24637315, -0.50579607,
 -0.45255361,  0.68012764, -0.2490138 , -0.95163741],
[-0.35152204, -0.29686815, -0.42892835, -0.57518294, -0.33777353,
 -0.4619151 , -0.28478573, -0.4129479 , -0.24553995, -0.36656949,
 -0.47419936, -0.53167338, -1.32807362,  0.03257095]])
```

In [161…

```
# Run kmeans with 2 clusters
kmeans = KMeans(n_clusters = 2, random_state = 42)
mod = kmeans.fit_predict(standard)
mod1 = mod+1
mod1
```

Out[161…

```
array([1, 1, 1, 1, 1, 2, 1, 1, 2, 1, 1, 1, 1])
```

In [162…

```
# Create cluster column
cluster = list(mod1)
df_cluster['Cluster']=cluster

# show dataframe
pd.set_option("display.max_rows",None,"display.max_columns", None)
df_cluster
```

Out[162…

	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
District Name									
New Forest	2531.0	987.0	1271.5	301.0	173.0	123.5	677.5	1159.5	795
East Hampshire	1693.0	491.0	647.0	170.5	103.5	60.5	321.0	664.5	497
Gosport	1936.5	267.5	690.5	172.5	111.5	90.0	409.5	604.5	279
Test Valley	1927.0	610.5	660.0	241.0	137.5	86.0	475.5	755.0	529
Hart	1134.0	264.0	402.0	95.5	70.5	44.5	142.5	484.0	338
Southampton	7123.5	1908.5	2839.0	1100.0	444.0	486.5	2191.5	3027.0	2452
Havant	2717.5	386.0	927.0	263.0	172.5	128.0	671.5	826.0	436
Rushmoor	2060.5	374.0	687.0	237.5	120.0	108.5	694.5	832.5	712

District Name	Anti-social & Public Order	Burglary & Robbery	Criminal damage and arson	Drugs	Other crime	Possession of weapons	Shoplifting	Theft	Vehic crim
Portsmouth	6380.5	1186.5	2337.5	862.0	343.5	417.5	2183.5	2408.5	1740
Fareham	1720.5	292.5	542.0	127.5	97.5	63.0	485.5	601.0	386
Basingstoke	3106.5	695.5	1166.0	339.0	222.5	159.0	690.5	1136.5	565
Winchester	2076.0	504.0	692.0	310.0	172.5	78.0	519.0	839.0	619
Eastleigh	2201.0	519.5	745.5	173.0	143.5	87.0	596.5	785.0	619

In [163…

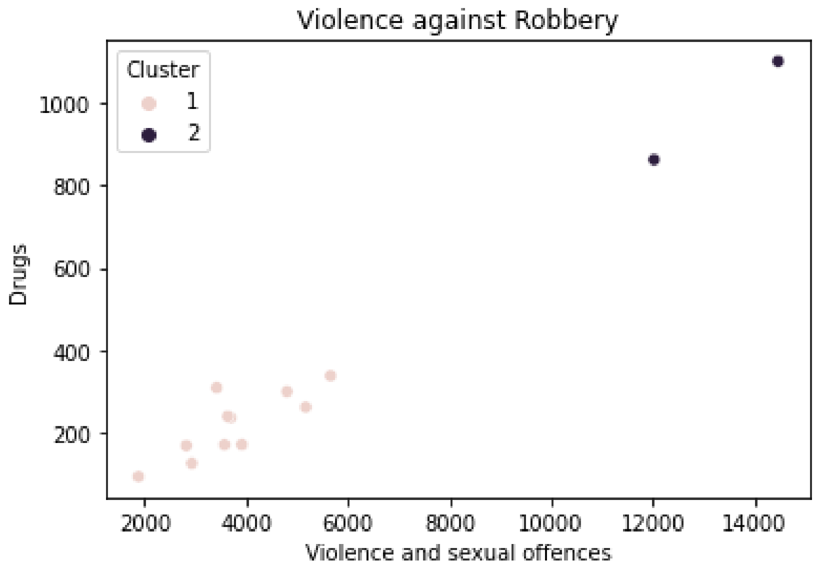
```
pd.DataFrame(df_cluster.iloc[:,14])
```

Out[163…

District Name	Cluster
New Forest	1
East Hampshire	1
Gosport	1
Test Valley	1
Hart	1
Southampton	2
Havant	1
Rushmoor	1
Portsmouth	2
Fareham	1
Basingstoke	1
Winchester	1
Eastleigh	1

In [91]:

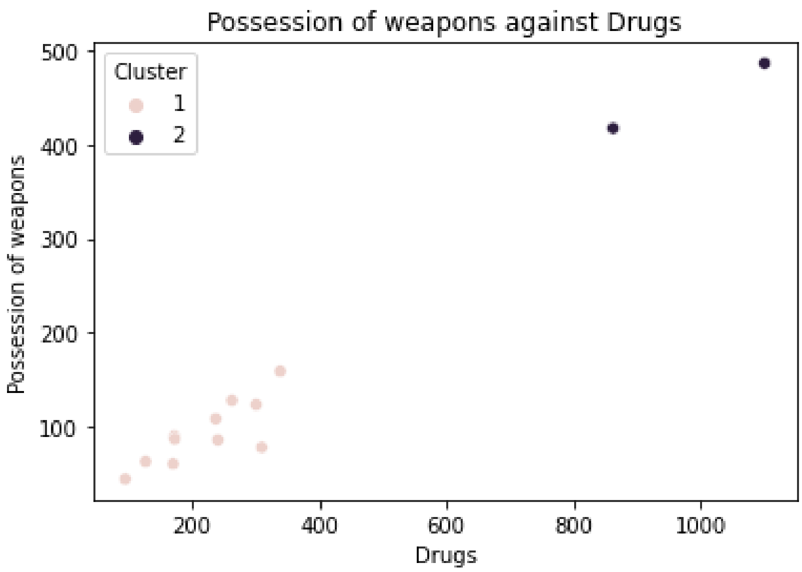
```
# Plot an example chart
sns.scatterplot(data = df_cluster, x = 'Violence and sexual offences', y = 'Dru
plt.title('Violence against Robbery');
```



We can see that there is a relationship between these two crimes and two points are well apart from the others

In [165…

```
# Another example
sns.scatterplot(data = df_cluster, x = 'Drugs', y = 'Possession of weapons', hu
plt.title('Possession of weapons against Drugs');
```



In [175…

```
# Extract the inertia values
inertias = []
mapping1 = {}

K = range(1, 10)

for k in K:
    kmeanModel = KMeans(n_clusters=k, random_state=42).fit(standard)

    inertias.append(kmeanModel.inertia_)
    mapping1[k] = inertias[-1]
```

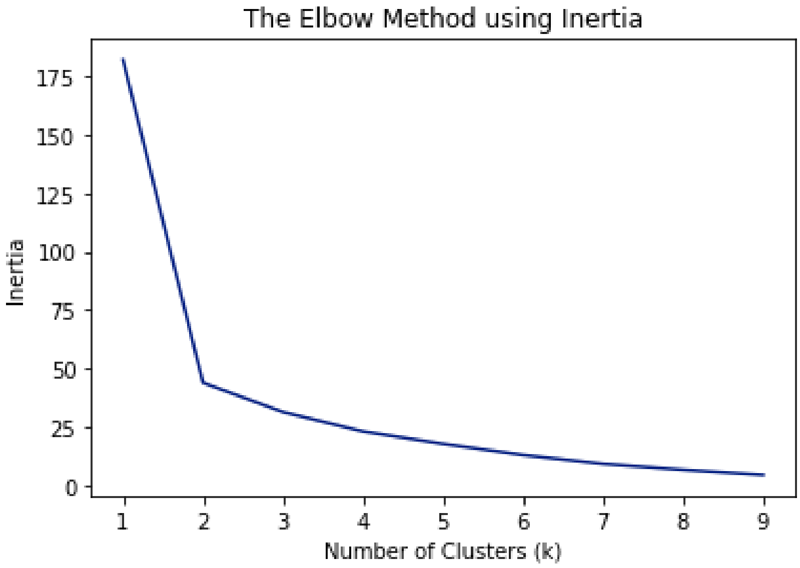
In [179…

```
# Elbow chart
print("Inertia values:")
for key, val in mapping1.items():
```

```
    print(f'{key} : {val}')

# Plotting the graph of k versus Inertia
plt.plot(K, inertias)
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()
```

```
Inertia values:
1 : 182.0
2 : 44.02906924134521
3 : 31.50050778438595
4 : 23.22084431051492
5 : 17.887145849250526
6 : 13.139855290055085
7 : 9.364786335010809
8 : 6.841716784621628
9 : 4.621016427311179
```



The connurbations of Portsmouth and Southampton are quite distinct from the other districts in Hampshire in terms of the level of crimes reported

Build predictive model for crime based on economic indicators

In [180…

```
# Select columns
data = crime_district_all[['Total', 'med_salary','unemp_rate','Pop_density']]
data = data.sample(frac = 1)
```

In [181…

```
# Look at correlations
data.corr()
```

Out[181…

	Total	med_salary	unemp_rate	Pop_density
Total	1.000000	-0.029852	0.737380	0.659380
med_salary	-0.029852	1.000000	-0.122282	-0.254994
unemp_rate	0.737380	-0.122282	1.000000	0.578733

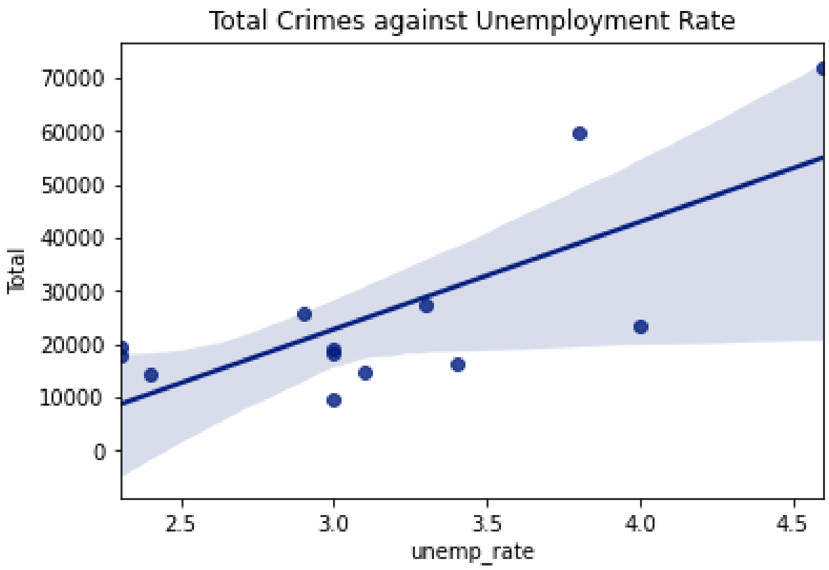
	Total	med_salary	unemp_rate	Pop_density
Pop_density	0.659380	-0.254994	0.578733	1.000000

There is a fairly strong correlations between the total crimes and unemployment rate and population density, such that higher population density and unemployment rates are correlated with higher number of crimes. The correlation with median salary is weak negative, such that a higher salary is correlated with a lower crime rate.

We will have a look at the plots

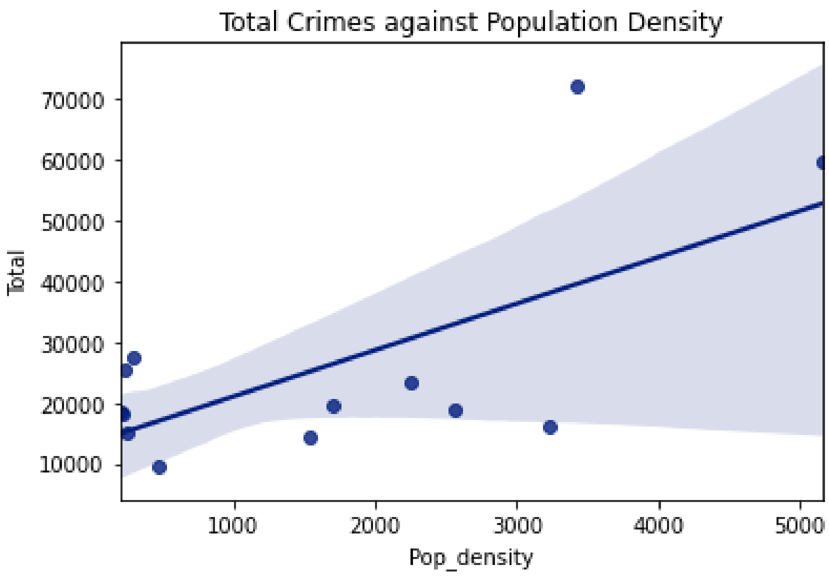
In [182...

```
sns.regplot(data = data, x = 'unemp_rate', y = 'Total')
plt.title('Total Crimes against Unemployment Rate');
```



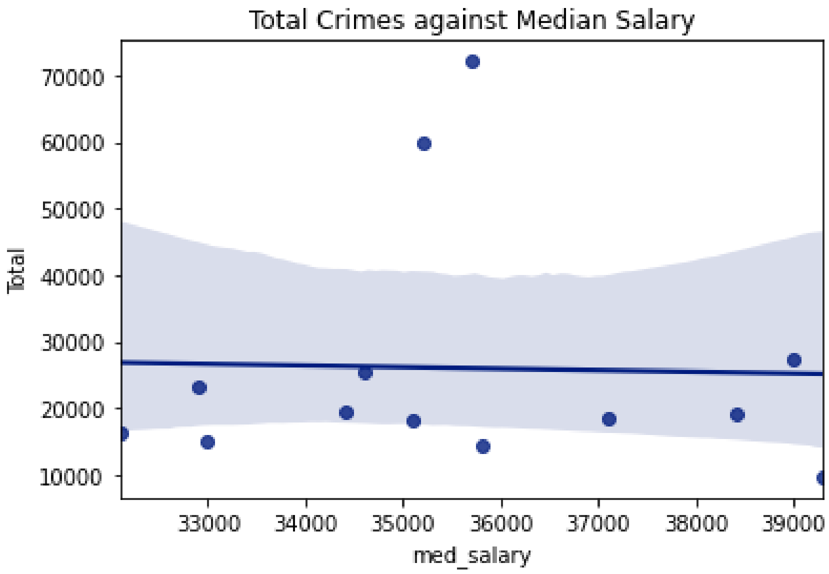
In [183...

```
sns.regplot(data = data, x = 'Pop_density', y = 'Total')
plt.title('Total Crimes against Population Density');
```



In [184...

```
sns.regplot(data = data, x = 'med_salary', y = 'Total')
plt.title('Total Crimes against Median Salary');
```



We will try to build a model but recognising that we have very few data points so it is unlikely to be a good model. We would need data from across the UK to build something we could rely upon. However, it is interesting to have a look

In [185…
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
```

In [207…
```
# Define X and y
X = data.drop(columns = ['Total'],axis = 1)
y = data["Total"].values # This is the average of 2022 and 2023
```

In [313…
```
# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.2, shuff
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(10, 3) (3, 3) (10,) (3,)
```

In [314…
```
scaler = StandardScaler()

# Fit on training and transform both training and test data
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [315…
```
# Fit the model
lr = LinearRegression()
lr.fit(X_train_scaled, y_train)
```

Out[315…
```
LinearRegression()
```

In [316…
```
# Print the coefficients and intercept
print(lr.coef_)
print(lr.intercept_)
```

```
[ 1332.28793535 11508.06382328  3466.8365124 ]
23671.7
```

In [317…

```
# Get the r-squared score on the training data
lr.score(X_train_scaled,y_train)
```

Out[317…

```
0.6584895969688469
```

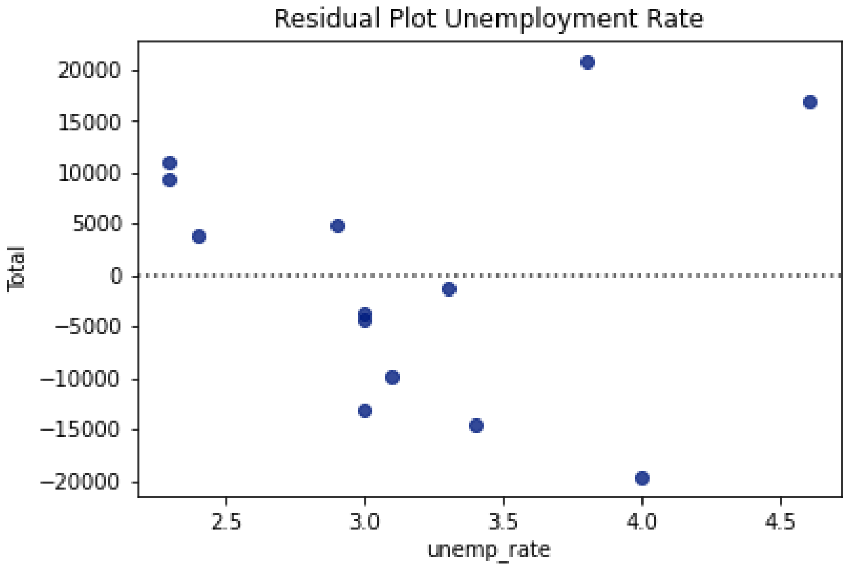
This is the percentage of the variation in crime which can be explained by the features of population density, median income and unemployment rate. The remaining percentage cannot be explained by our model.

In [318…

```
# Residual plot
sns.residplot(data['med_salary'],data['Total'])
plt.title('Residual Plot Median Salary');
```

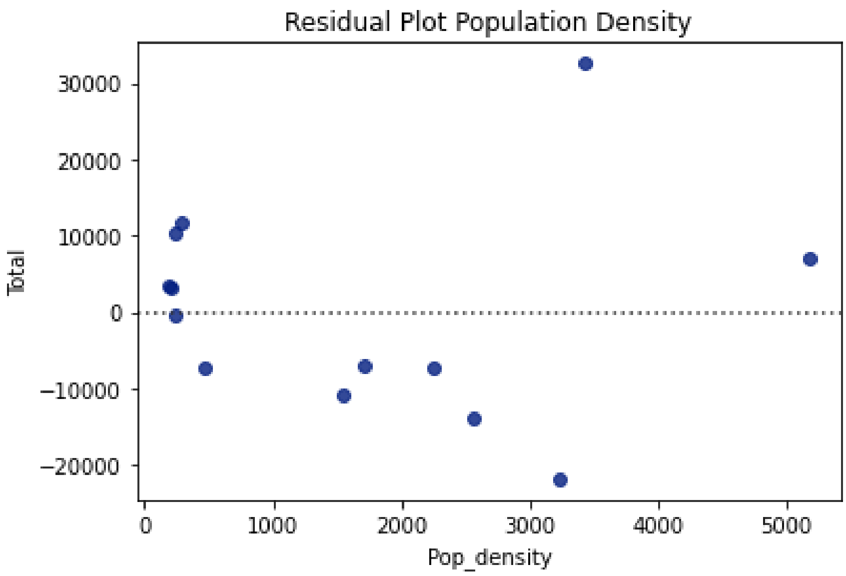
In [319…

```
# Residual plot
sns.residplot(data['unemp_rate'],data['Total'])
plt.title('Residual Plot Unemployment Rate');
```



In [320…

```
# Residual plot
sns.residplot(data['Pop_density'],data['Total'])
plt.title('Residual Plot Population Density');
```



We are looking for the residuals to be randomly spread around the X axis. It is a bit difficult to tell, especially with so few points.

In [321…

```
y_pred = lr.predict(X_test_scaled)
y_pred
```

Out[321…

```
array([48665.55012988, 28835.60545012, 42477.48550632])
```

In [322…

```
y_test
```

Out[322…

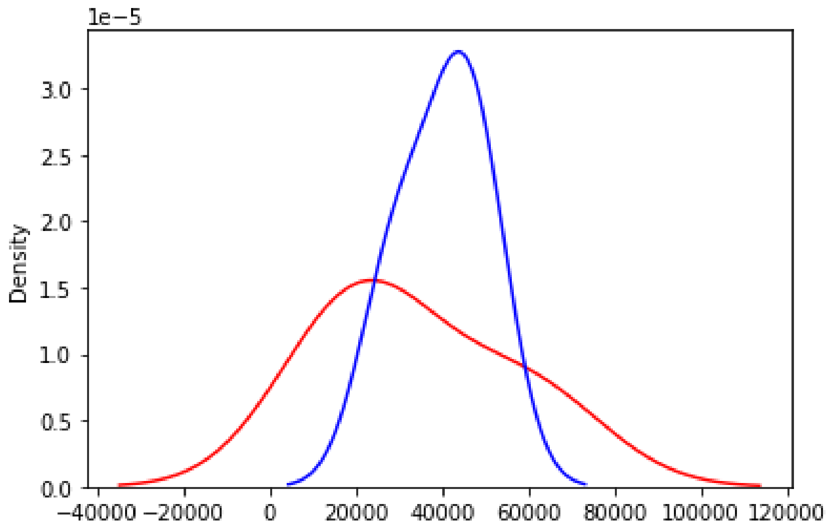
```
array([59762., 19045., 23393.])
```

In [323…

```
# Kde or distplot, y_pred against
sns.distplot(y_test, hist = False, color = 'r', label = 'Actual Value')
sns.distplot(y_pred, hist = False, color = 'b', label = 'Predicted Value')
;
```

Out[323…

```
''
```



In [324…

```
# Get mean squared error
mse = mean_squared_error(y_test, y_pred)
print('The mean square error of price and predicted value is: ', mse)
```

```
The mean square error of price and predicted value is:  194401580.61361882
```

In [325…

```
# Get r-squared
r_squared = r2_score(y_test, y_pred)
print('The R-square value is: ', r_squared)
```

```
The R-square value is:  0.4166948040603897
```

This is quite a poor predictive model, explaining little more than we would expect by chance. A much bigger sample size would be needed to build a model and make reliable conclusions about crime levels being related to the features we identified and likely a whole host of different predictor variables would be needed making this quite a complicated model.

In [ ]:

```

```