Brexit: What divided Britain?

Author: Harry Bell

Email: hjb328@stern.nyu.edu (hjb328@stern.nyu.edu)

Introduction

On the 23rd June 2016, the United Kindgom voted to leave the European Union. It was a result that was completely unexpected and illustrated how divide Britain had become. The brexit debate centered around immigration and the economy. After the result, pro-remain voters adamantly believed that the country had chosen to leave due to immigration fears. It was perceived that xenophobia was the main factor in the result.

In this report I analyze immigration, lifestyle, and economic data by Constituency to determine the main factors in the Brexit Vote.

My report will be broken into four sections:

- Data Report
- Description of packages used
- Analysis of data
- Conclusion

Data Report

My data for this project came from the UK 2011 Census (https://www.ons.gov.uk/census/2011census). The census provides very detailed information about UK citizens and is displayed via numerous regional breakdowns. For my report, I used data gathered by 2010 parlimentary constituencies to ensure consistency, and to allow for accurate comparison of information. With 650 constituencies in the UK, the information gathered can show trends and patterns.

All my data is saved as .csv files. The datasets are stored in my github repository and are imported via url. I used pd.read_csv(url) to import all the datasets.

To allow for easy comparison, I created a master Dataframe to store all the data I wanted to analyze. When I imported the individual datasets, I took the keys I needed to analyze and copied them into the masterDf. The masterDf is ordered alphabetically by constituency to ensure that all the copied cells are matched to the correct constituency.

Packages

My packages are as follows:

- **pandas**: Used to import, store, and alter data
- **matplotlib**: Used to plot data onto graphs
- **matplotlib.pyplot**: Create lines of best fit for graphs
- **numpy**: Transformation of data

In [710]:
```
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import numpy as np
```

Brexit Vote Results

In [711]:
```
# Import Data on voting results
euVoteDf = pd.read_csv("https://raw.githubusercontent.com/harryb328/Data
_Bootcamp_Final_Project/master/eureferendum_constitunecy.csv")

# Set Index
euVoteDf = euVoteDf.set_index(["ONS ID"])

#Order alphabetically by constituency
euVoteDf = euVoteDf.sort_values(by='Constituency', ascending=True)
```

In [712]:
```
#Permantly delete column
del euVoteDf['estimate']
```

In [713]:
```
#Permantly delete column
del euVoteDf['result']
```

In [714]:
```
#Permantly delete column
del euVoteDf['leave']
```

In [715]:
```
#Rename column
euVoteDf=euVoteDf.rename(columns = {'FIGURE TO USE':'Pct_leave'})

#Display
euVoteDf.head()
```

Out[715]:

	Constituency	Pct_leave
ONS ID		
W07000049	Aberavon	0.601
W07000058	Aberconwy	0.522
S14000001	Aberdeen North	0.431
S14000002	Aberdeen South	0.321
S14000003	Airdrie and Shotts	0.398

Demographics by Ethnicity

In [716]:
```
# Import Data on ethnic demographics
urlEthnicGroup = "https://raw.githubusercontent.com/harryb328/Data_Bootc
amp_Final_Project/master/Ethnic%20Group%20By%20Constituency%20.csv"
ethnicGroupDf = pd.read_csv(urlEthnicGroup)

#Display first 5 rows
ethnicGroupDf.head()
```

Out[716]:

	date	geography	geography code	Ethnic Group: All categories: Ethnic group; measures: Value	Ethnic Group: White; measures: Value	Ethnic Group: Gypsy / Traveller / Irish Traveller; measures: Value	Ethnic Group: Mixed / Multiple ethnic group; measures: Value	Ethni Grou Asian Asia Britisl Indiar measures Valu
0	2011	Berwick-upon-Tweed	E14000554	75718	74648	50	373	131
1	2011	Bishop Auckland	E14000569	87143	85935	123	461	147
2	2011	Blaydon	E14000574	88281	86665	27	504	245
3	2011	Blyth Valley	E14000575	82174	81061	10	442	199
4	2011	City of Durham	E14000641	94375	90029	106	994	616

In [717]:
```
# Rename colunms to more simple names
ethnicGroupDf=ethnicGroupDf.rename(columns = {'Ethnic Group: All categor
ies: Ethnic group; measures: Value':'Total_Population'})

#Create new dataframe with specfic columns from ethnicGroupDf
ethnicNonWhiteDf = ethnicGroupDf[['geography code','geography','Total_Po
pulation','Ethnic Group: Non White', "Percentage of non-Whites"]].copy()

#Set index
ethnicNonWhiteDf = ethnicNonWhiteDf.set_index(['geography code'])

#Order alphabetically by constituency
ethnicNonWhiteDf = ethnicNonWhiteDf.sort_values(by='geography', ascendin
g=True)

#Display
ethnicNonWhiteDf.head()
```

Out[717]:

	geography	Total_Population	Ethnic Group: Non White	Percentage of non-Whites
geography code				
W07000049	Aberavon	66133	1684	0.025
W07000058	Aberconwy	56415	1245	0.022
S14000001	Aberdeen North	99654	9940	0.100
S14000002	Aberdeen South	93197	7018	0.075
S14000003	Airdrie and Shotts	85845	1400	0.016

Create Master Dataframe

In [718]:
```
# Create masterDf by joing existing dataframes
#Use this dataframe for the project to store information
masterDf = euVoteDf.join(ethnicNonWhiteDf)
```

In [719]:
```
#Delete replicated geography column
del masterDf['geography']
```

In [720]:
```
#Rename column
masterDf=masterDf.rename(columns = {'Percentage of non-Whites':'Pct_non_
whites'})
```

In [721]:
```
#Create column to display whether a constituency voted majority remain o
r leave
# Leave is stored as 1 and remain is stored as 0

# list to store data
l =[]

#loop through all rows in percentage leave column
for x in masterDf["Pct_leave"] :

    #if the pct_leave greater than 0.5 then constituency voted to leave:
 stored as 1
    if x > 0.50:

        #add to list l
        l.append(1)

    #if the pct_leave less than 0.5 then constituency voted to remain: s
tored as 0
    else:

        #add to list l
        l.append(0)

#Create column in masterDf using data stored in list l
masterDf["leave"] = l
```

In [722]:
```
#Create column to show which constituencies are in london
masterDf["London"] = 0

#Constuencies in London
x = ['E14000540',
'E14000549',
'E14000551',
'E14000553',
'E14000555',
'E14000558',
'E14000591',
'E14000592',
'E14000593',
'E14000604',
'E14000615',
'E14000621',
'E14000629',
'E14000634',
'E14000636',
'E14000639',
'E14000654',
'E14000655',
'E14000656',
'E14000657',
'E14000673',
'E14000674',
'E14000675',
'E14000676',
'E14000679',
'E14000687',
'E14000690',
'E14000691',
'E14000692',
'E14000696',
'E14000701',
'E14000703',
'E14000718',
'E14000720',
'E14000721',
'E14000726',
'E14000727',
'E14000731',
'E14000732',
'E14000737',
'E14000741',
'E14000750',
'E14000751',
'E14000752',
'E14000759',
'E14000760',
'E14000763',
'E14000764',
'E14000768',
'E14000770',
'E14000787',
'E14000788',
```

```
'E14000789',
'E14000790',
'E14000823',
'E14000869',
'E14000872',
'E14000882',
'E14000887',
'E14000896',
'E14000900',
'E14000906',
'E14000978',
'E14000984',
'E14000998',
'E14001002',
'E14001005',
'E14001007',
'E14001008',
'E14001013',
'E14001032',
'E14001036',
'E14001040']

#Loop through each row in the master dataframe
for i in x:

    #If index in list above is found change London value to 1
    masterDf.loc[i,"London"] = 1

#Display
masterDf.tail()
```

Out[722]:

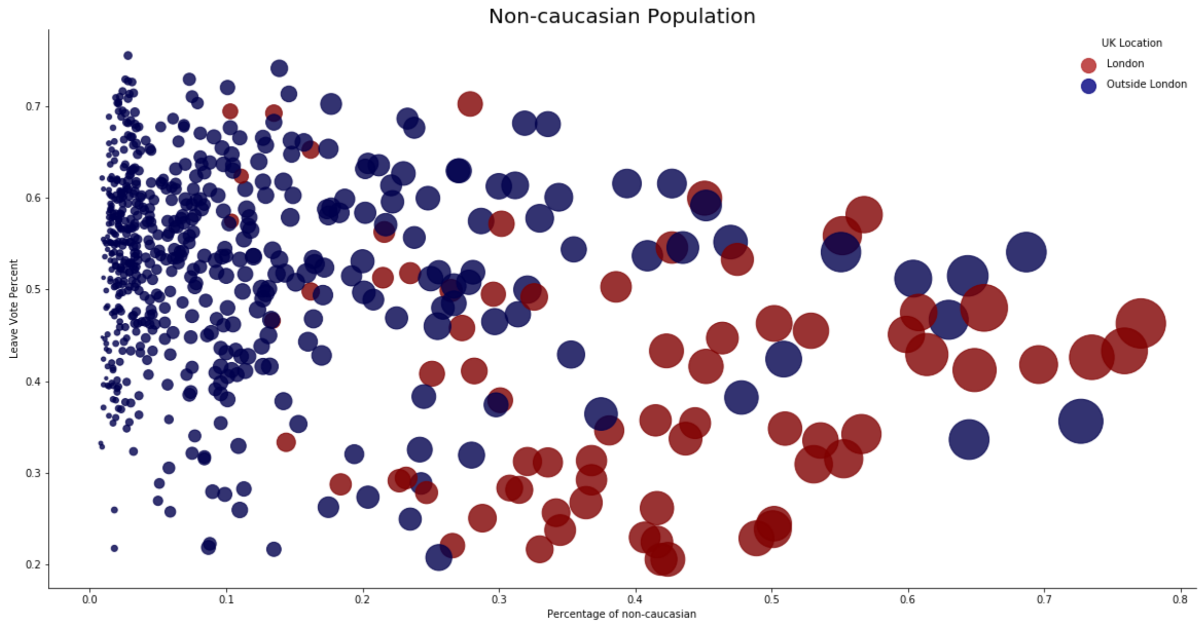
	Constituency	Pct_leave	Total_Population	Ethnic Group: Non White	Pct_non_whites	leave	Lo
ONS ID							
E14001059	Wythenshawe and Sale East	0.496	105438	13614	0.129	0	0
E14001060	Yeovil	0.599	106783	2393	0.022	1	0
W07000041	Ynys Mon	0.509	69751	1296	0.019	1	0
E14001061	York Central	0.388	104359	7773	0.074	0	0
E14001062	York Outer	0.447	93692	3816	0.041	0	0

Demographics Analysis

In this first analyiss, I will look at ethnic diversity in each constituency and the number of foreign born individuals. I will use a scatter plot to plot each constituencies result against its own leave vote.

My hypothesis is that actual immigration numbers had little to no effect on the vote.

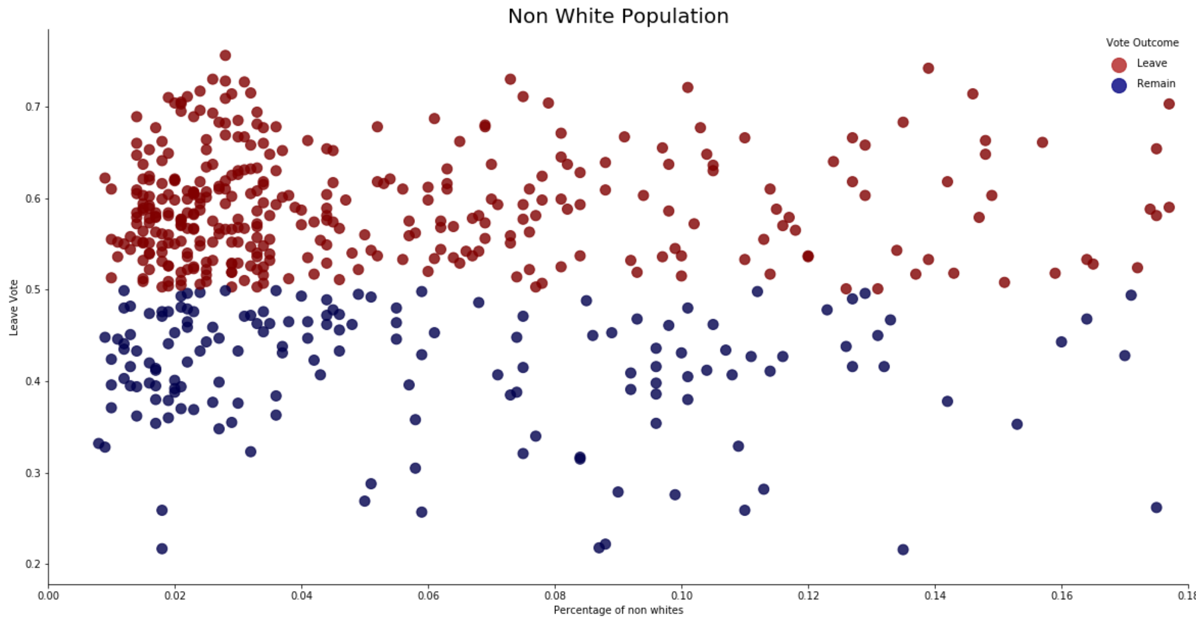
In [723]:
```
# Create figure
fig, ax = plt.subplots(figsize = (20,10))

# Custom legend for dot color
for area in ["l", "n"]:

    #for london dot
    if area =="l":

        #create london dot for legend
        ax.scatter([], [], c='firebrick', alpha=0.8, s=200,
                   label= "London")

    #for outside london
    else:

        #create outside lonodon dot
        ax.scatter([], [], c='navy', alpha=0.8, s=200,
                label= "Outside London")

#Create legend
ax.legend(frameon=False, labelspacing=1, title='UK Location')

#Size of each dot determined by absolute number of non-caucasians in eac
h area
size = masterDf['Ethnic Group: Non White']/50

#Different color for in and outside london
color = masterDf['London']

#color map
cmap = "seismic"

#Create Scatter plot
ax.scatter(masterDf['Pct_non_whites'], masterDf['Pct_leave'],s = size, c
 = color ,alpha = 0.8, cmap = cmap)

#Labels
ax.set_title("Non-caucasian Population", fontsize = 20)
ax.set_ylabel("Leave Vote Percent", fontsize = 10)
ax.set_xlabel("Percentage of non-caucasian", fontsize = 10)


#Remove Spines
ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)
```



The graph shows the the non-caucasian population is concentrated in certain areas. The reds dots show regions in london, while Blue is outside london. This shows that most of the non-caucasian population is in London. For the rest of the demographics analyis I will remove London constituencies to focus on the outer areas

In [724]:
```
#Excluded London from dataset
x = masterDf.loc[masterDf['London'] == 0, 'Pct_non_whites']
y = masterDf.loc[masterDf['London'] == 0, 'Pct_leave']
z = masterDf.loc[masterDf['London'] == 0, 'leave']
```

In [725]:
```
# Create figure
fig, ax = plt.subplots(figsize = (20,10))

# Custom legend for dot color
for area in ["l", "r"]:

    #for leave dot
    if area =="l":

        #Create leave dot
        ax.scatter([], [], c='firebrick', alpha=0.8, s=200,
                        label= "Leave")

    #for remain dot
    else:

        #Create remain dot
        ax.scatter([], [], c='navy', alpha=0.8, s=200,
                    label= "Remain")

#Create legend
ax.legend(frameon=False, labelspacing=1, title='Vote Outcome')

#color for leave and remain
color = z

#Color map
cmap = "seismic"

#Create scatter plot
ax.scatter(x, y,s = 100, c = color ,alpha = 0.8, cmap = cmap)

#Create Labels
ax.set_title("Non White Population", fontsize = 20)
ax.set_ylabel("Leave Vote", fontsize = 10)
ax.set_xlabel("Percentage of non whites", fontsize = 10)

#x axis limit to 18%
ax.set_xlim(0,0.18)

#Remove Spines
ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)
```



Areas that are overwhelmingly white (> 82%) still mostly voted to leave the EU. The number of non-white residents had little effect on the vote, there is no real correlation.

UK Migration

In [726]:
```
#Import data
countryBirthUrl ="https://raw.githubusercontent.com/harryb328/Data_Bootc
amp_Final_Project/master/Country_of_birth_by_constituency.csv"
countryBirthDf = pd.read_csv(countryBirthUrl)

#Set index and order
countryBirthDf = countryBirthDf.sort_values(by='geography', ascending=Tr
ue)
countryBirthDf = countryBirthDf.set_index(['geography code'])

#Display
countryBirthDf.head()
```

Out[726]:

	geography	Total	UK	Ireland	Europe	EU (ex.Ireland)	Germany	Lithuania	F
geography code									
W07000049	Aberavon	66133	64237	244	587	536	157	2	1
W07000058	Aberconwy	56415	53839	418	1050	969	166	15	3
S14000001	Aberdeen North	99654	80833	598	8939	8321	818	545	4
S14000002	Aberdeen South	93197	78570	718	6069	5445	551	256	2
S14000003	Airdrie and Shotts	85845	83605	136	1092	1059	121	17	7

In [727]:
```
#Add percentages for different regions to the master dataframe
for x in countryBirthDf:
    if x != "geography":
        y = "Pct_" + x
        masterDf[y] = countryBirthDf[x]/countryBirthDf["Total"]
masterDf.head()
```

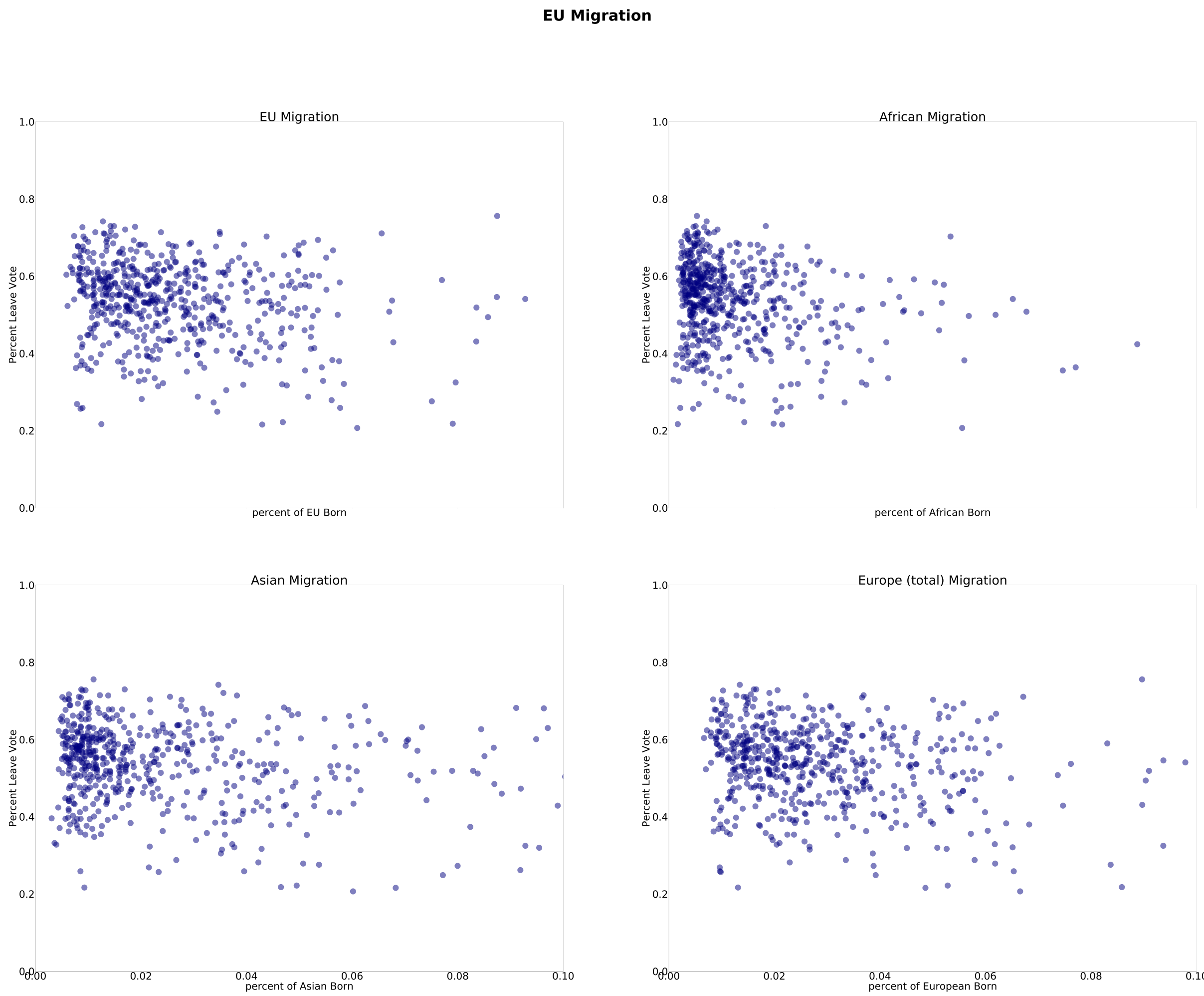
Out[727]:

	Constituency	Pct_leave	Total_Population	Ethnic Group: Non White	Pct_non_whites	leave	L
ONS ID							
W07000049	Aberavon	0.601	66133	1684	0.025	1	0
W07000058	Aberconwy	0.522	56415	1245	0.022	1	0
S14000001	Aberdeen North	0.431	99654	9940	0.100	0	0
S14000002	Aberdeen South	0.321	93197	7018	0.075	0	0
S14000003	Airdrie and Shotts	0.398	85845	1400	0.016	0	0

In [728]:
```
#Excluded london locations
w = masterDf.loc[masterDf['London'] == 0, 'Pct_EU (ex.Ireland)']
x = masterDf.loc[masterDf['London'] == 0, 'Pct_Africa']
y = masterDf.loc[masterDf['London'] == 0, 'Pct_Middle East and Asia']
z = masterDf.loc[masterDf['London'] == 0, 'Pct_Europe']
l = masterDf.loc[masterDf['London'] == 0, 'Pct_leave']
```

In [729]:
```
#Create figure
fig, ax = plt.subplots(nrows = 2, ncols = 2, sharex = True, figsize = (2
00,150))

#4 by 1 array
ax = ax.ravel()

#List of data to plot
var_list = [w,x,y,z]
name = ["EU Migration", "African Migration", "Asian Migration", "Europe
 (total) Migration"]
xaxis = ["EU Born","African Born", 'Asian Born', "European Born"]


#Iteration count
count = 0

for data in ax:



    #Create scatter plots
    data.scatter(var_list[count],l, alpha = 0.50, s = 3200, c ='navy') #
 Scatter plot


    #remove spines
    data.spines["right"].set_visible(False)
    data.spines["top"].set_visible(False)

    #labels
    data.set_title(name[count], fontsize = 120)
    data.set_ylabel("Percent Leave Vote", fontsize = 96)
    data.set_xlabel("percent of " + xaxis[count], fontsize = 96)

    #set axis limits
    data.set_xlim(0,0.1)
    data.set_ylim(0,1)

    #tick size
    data.tick_params(axis = 'both', which = 'major', labelsize = 96)

    #increase count
    count = count + 1

#title
fig.suptitle("EU Migration", fontsize = 144, fontweight = "bold")
```

Out[729]: Text(0.5,0.98,'EU Migration')



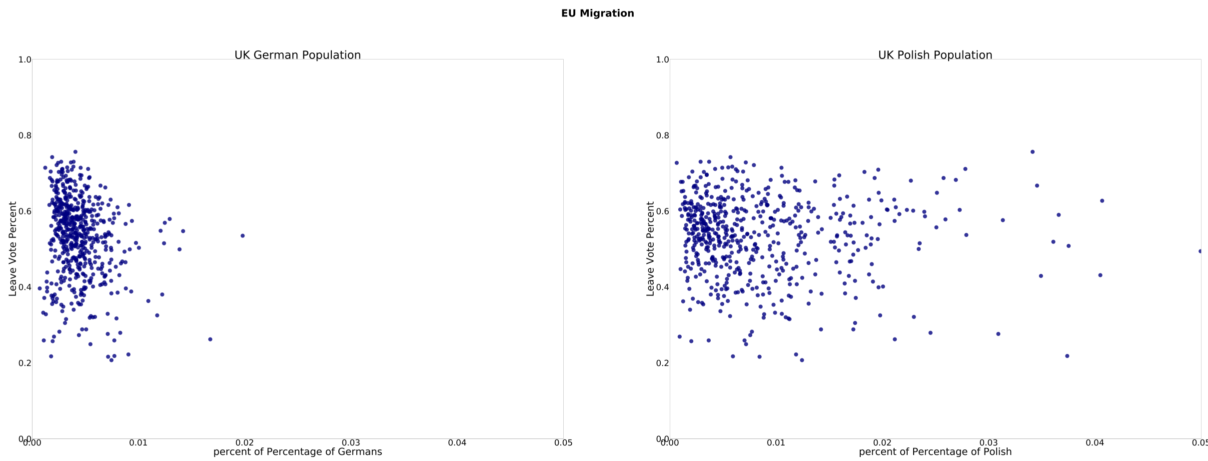
This shows that there is no correlation between the number of people born in foreign countries and the vote in that constituency. Most areas have a small percentage of foreign born citizens and yet still voted to leave the EU

In [730]:

```
#Exclude London
x = masterDf.loc[masterDf['London'] == 0, 'Pct_Germany']
y = masterDf.loc[masterDf['London'] == 0, 'Pct_Poland']
l = masterDf.loc[masterDf['London'] == 0, 'Pct_leave']
```

In [731]:
```
#Create figure
fig, ax = plt.subplots(ncols = 2, sharex = True, figsize = (300,100))


#Datasets
var_list = [x,y]
title_name = ["UK German Population", "UK Polish Population"]
x_name = ["Percentage of Germans","Percentage of Polish"]



#Iteration Count
count = 0

for data in ax:

    #Create scatter plots
    data.scatter(var_list[count],l, color = "navy",alpha = 0.80, s = 320
0)

    #Remove spines
    data.spines["right"].set_visible(False)
    data.spines["top"].set_visible(False)

    #Set labels
    data.set_ylabel("Leave Vote Percent", fontsize = 140)
    data.set_title(title_name[count], fontsize = 160)
    data.set_xlabel("percent of " + x_name[count], fontsize = 140)

    #Limits
    data.set_xlim(0,0.05)
    data.set_ylim(0,1)

    #tick size
    data.tick_params(axis = 'both', which = 'major', labelsize = 120)

    #count increase
    count = count + 1

#title
fig.suptitle("EU Migration", fontsize = 144, fontweight = "bold") # big
 titel
```

```
Out[731]: Text(0.5,0.98,'EU Migration')
```



Economic and Social Analysis

Employment By Industry

```
In [732]: # Import data
industryUrl ="https://raw.githubusercontent.com/harryb328/Data_Bootcamp_
Final_Project/master/Industry%20by%20Constituency.csv"
industryDf = pd.read_csv(industryUrl)

# Create new dataframe from useful columns in industryDf
industrySectorDf = industryDf[["geography code","geography","Pct_primary
 ","Pct_manufactoring ","Pct_M.tech","Pct_utilities","Pct_construction",
"Pct_L_Services","Pct_H_Services","Pct_Govt","Pct_Arts","Pct_Other"]]

# Set index
industrySectorDf = industrySectorDf.set_index(["geography code"])
```

```
In [733]: #Consolidate maunfacuring sectors into one
industrySectorDf['Pct_Manufacture'] = industrySectorDf['Pct_manufactorin
g '] + industrySectorDf['Pct_M.tech'] + industrySectorDf["Pct_utilities"
]+industrySectorDf["Pct_construction"]
```

```
In [734]: #Consolidate service sectors
industrySectorDf["Pct_service"] = 1 - industrySectorDf["Pct_primary "] -
 industrySectorDf["Pct_Manufacture"]
```

```
In [735]: #Place column in master
masterDf["Pct_primary"] = industrySectorDf["Pct_primary "]
```

```
In [736]: #Place column in master
masterDf["Pct_manufacturing"] = industrySectorDf["Pct_Manufacture"]
```

In [737]:
```
#Place column in master
masterDf["Pct_service"] = industrySectorDf["Pct_service"]

#Display
masterDf.head()
```

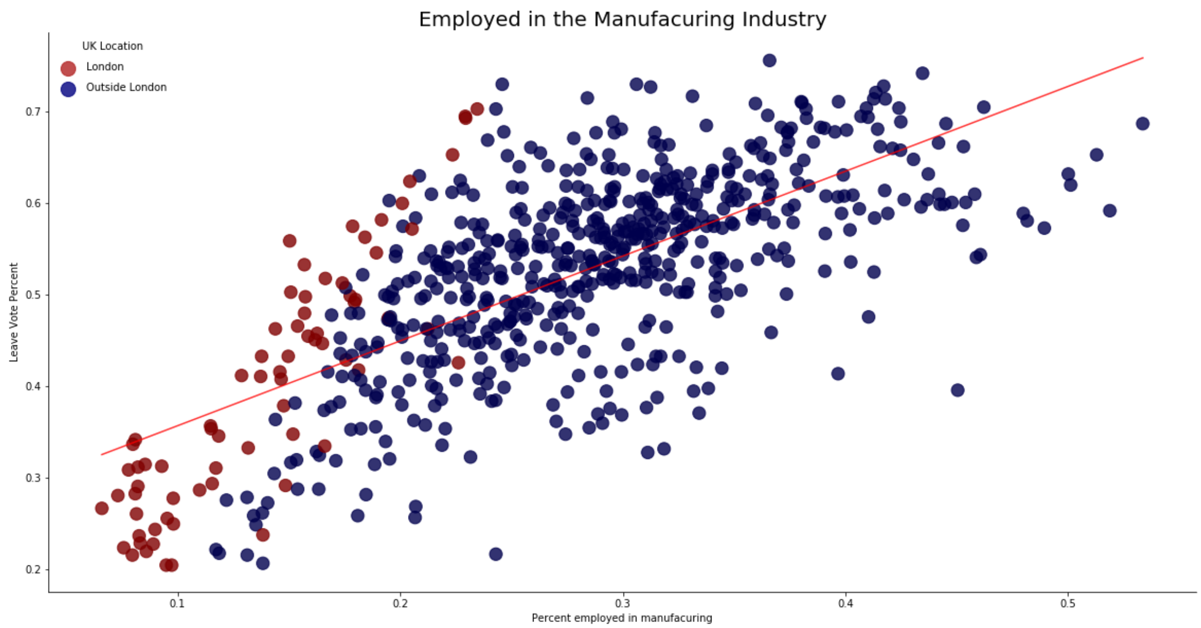
Out[737]:

	Constituency	Pct_leave	Total_Population	Ethnic Group: Non White	Pct_non_whites	leave	Le
ONS ID							
W07000049	Aberavon	0.601	66133	1684	0.025	1	0
W07000058	Aberconwy	0.522	56415	1245	0.022	1	0
S14000001	Aberdeen North	0.431	99654	9940	0.100	0	0
S14000002	Aberdeen South	0.321	93197	7018	0.075	0	0
S14000003	Airdrie and Shotts	0.398	85845	1400	0.016	0	0

5 rows × 21 columns

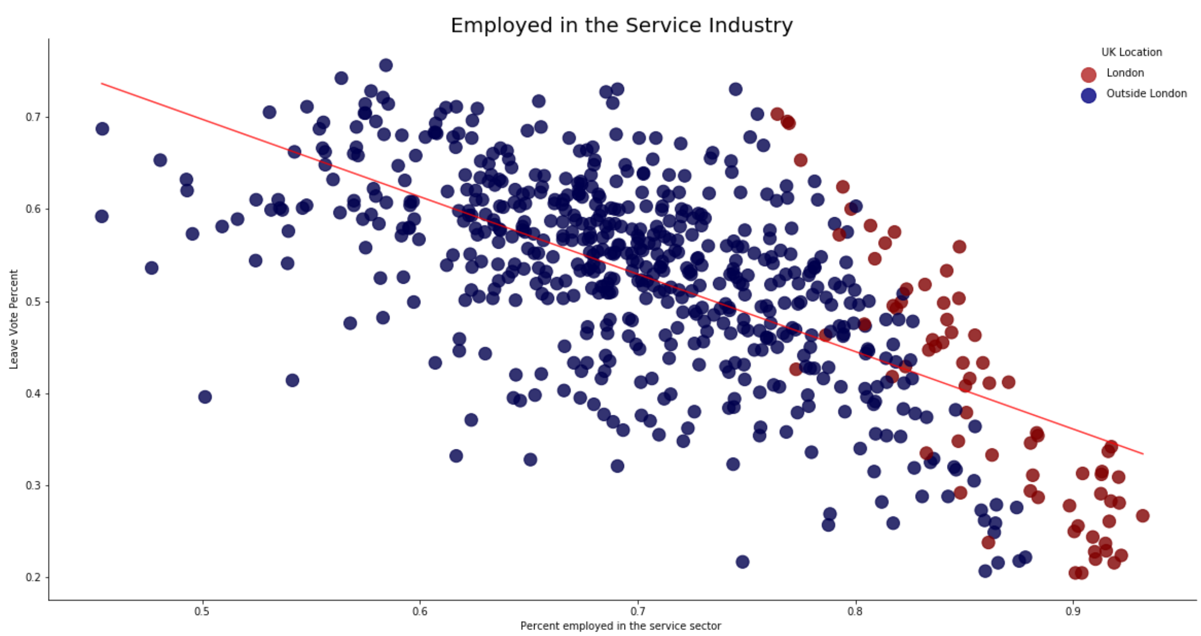
In [738]:
```
fig, ax = plt.subplots(figsize = (20,10))


#Custom legend
for area in ["l", "n"]:
    if area =="l":
        ax.scatter([], [], c='firebrick', alpha=0.8, s=200,
                        label= "London")
    else:
        ax.scatter([], [], c='navy', alpha=0.8, s=200,
                    label= "Outside London")
ax.legend(frameon=False, labelspacing=1, title='UK Location')

#color and color map
color = masterDf['London']
cmap = "seismic"

#Create Scatter
ax.scatter(masterDf['Pct_manufacturing'], masterDf['Pct_leave'],s = 150,
 alpha = 0.8, c = color, cmap = cmap)

#Remove spines
ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

#Labels
ax.set_title("Employed in the Manufacuring Industry", fontsize = 20)
ax.set_ylabel("Leave Vote Percent", fontsize = 10)
ax.set_xlabel("Percent employed in manufacuring", fontsize = 10)
ax.tick_params(axis = 'both', which = 'major', labelsize = 10)

#Line of best fit
x = masterDf['Pct_manufacturing']
y = masterDf['Pct_leave']
ax.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.unique(x)), c =
"r",alpha = 0.8)
```

```
Out[738]: [<matplotlib.lines.Line2D at 0x14be1e3c8>]
```



In [739]:
```
fig, ax = plt.subplots(figsize = (20,10))

for area in ["l", "n"]:
    if area =="l":
        ax.scatter([], [], c='firebrick', alpha=0.8, s=200,
                      label= "London")
    else:
        ax.scatter([], [], c='navy', alpha=0.8, s=200,
                  label= "Outside London")
ax.legend(frameon=False, labelspacing=1, title='UK Location')


color = masterDf['London']
cmap = "seismic"


ax.scatter(masterDf['Pct_service'], masterDf['Pct_leave'],s = 150, alpha
 = 0.8, c = color, cmap = cmap)


ax.spines["right"].set_visible(False) # remove the top and right spines

ax.spines["top"].set_visible(False) # Same as above
ax.set_title("Employed in the Service Industry", fontsize = 20)
ax.set_ylabel("Leave Vote Percent", fontsize = 10)
ax.set_xlabel("Percent employed in the service sector ", fontsize = 10)
ax.tick_params(axis = 'both', which = 'major', labelsize = 10)

x = masterDf['Pct_service']
y = masterDf['Pct_leave']

ax.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.unique(x)), c =
"r",alpha = 0.8)
```

Out[739]: [<matplotlib.lines.Line2D at 0x14f700048>]



There is a strong correlation between the dominating industry in an area and voting result. Those areas with higher manufacturing had a higher leave vote percentage. Manufacturing jobs generally held by individuals from lower socio economic communites. What is particulary intriguing is that this replicated in London itself. Areas in London (red dots) with more manufacuring voted in favor of leaving EU.

Education

In [740]:
```
# import
educationUrl ="https://raw.githubusercontent.com/harryb328/Data_Bootcamp
_Final_Project/master/Qualifications_by_Constituency.csv"
educationDf = pd.read_csv(educationUrl)
eductionDf = educationDf.sort_values(by='geography', ascending=True)
educationDf = educationDf.set_index(['geography code'])
del educationDf['date']
```

In [741]:
```
educationDf.head()
```

Out[741]:

	geography	Total	No qualifications	Level 1 qualifications	Level 2 qualifications	Level 3 qualifications
geography code						
E14000554	Berwick-upon-Tweed	63866	15354	8569	10599	7205
E14000569	Bishop Auckland	72102	21622	9695	11612	8745
E14000574	Blaydon	72958	18535	10316	11813	8577
E14000575	Blyth Valley	67289	17260	10664	11868	8797
E14000641	City of Durham	80604	16489	8481	10664	15920

In [742]:
```
#Put percentages of data in master dataframe
for x in educationDf:
    if x != "geography":
        y = "Pct_" + x
        masterDf[y] = educationDf[x]/educationDf["Total"]
```

In [743]:
```
masterDf.head()
```

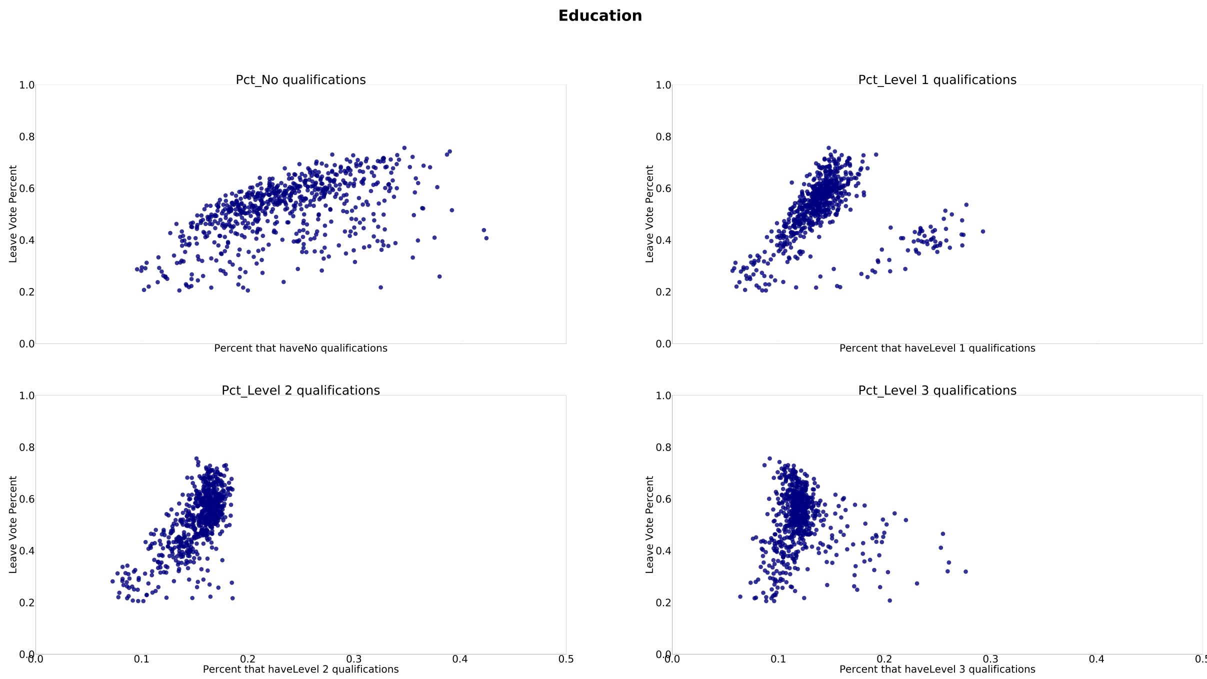
Out[743]:

	Constituency	Pct_leave	Total_Population	Ethnic Group: Non White	Pct_non_whites	leave	Le
ONS ID							
W07000049	Aberavon	0.601	66133	1684	0.025	1	0
W07000058	Aberconwy	0.522	56415	1245	0.022	1	0
S14000001	Aberdeen North	0.431	99654	9940	0.100	0	0
S14000002	Aberdeen South	0.321	93197	7018	0.075	0	0
S14000003	Airdrie and Shotts	0.398	85845	1400	0.016	0	0

5 rows × 26 columns

In [744]:
```
#Create figure
fig, ax = plt.subplots(nrows = 2, ncols = 2, sharex = True, figsize = (2
00,100))

#4 in 1
ax = ax.ravel()

#dataset
var_list = ["Pct_No qualifications","Pct_Level 1 qualifications", "Pct_L
evel 2 qualifications", "Pct_Level 3 qualifications"]
name = ["No qualifications", "Level 1 qualifications", "Level 2 qualific
ations", "Level 3 qualifications"]

#Iteration
count = 0

#Loop through data
for data in ax:



    #Create scatter
    data.scatter(masterDf[var_list[count]],masterDf["Pct_leave"],color =
 'navy', alpha = 0.80, s = 1600) # Scatter plot




    data.spines["right"].set_visible(False)
    data.spines["top"].set_visible(False)


    data.set_ylabel('Leave Vote Percent', fontsize = 96)
    data.set_xlabel("Percent that have" + name[count], fontsize = 96)
    data.set_title(var_list[count], fontsize = 120)

    data.set_xlim(0,0.5)
    data.set_ylim(0,1)

    data.tick_params(axis = 'both', which = 'major', labelsize = 96)

    count = count + 1

fig.suptitle("Education", fontsize = 144, fontweight = "bold")
```

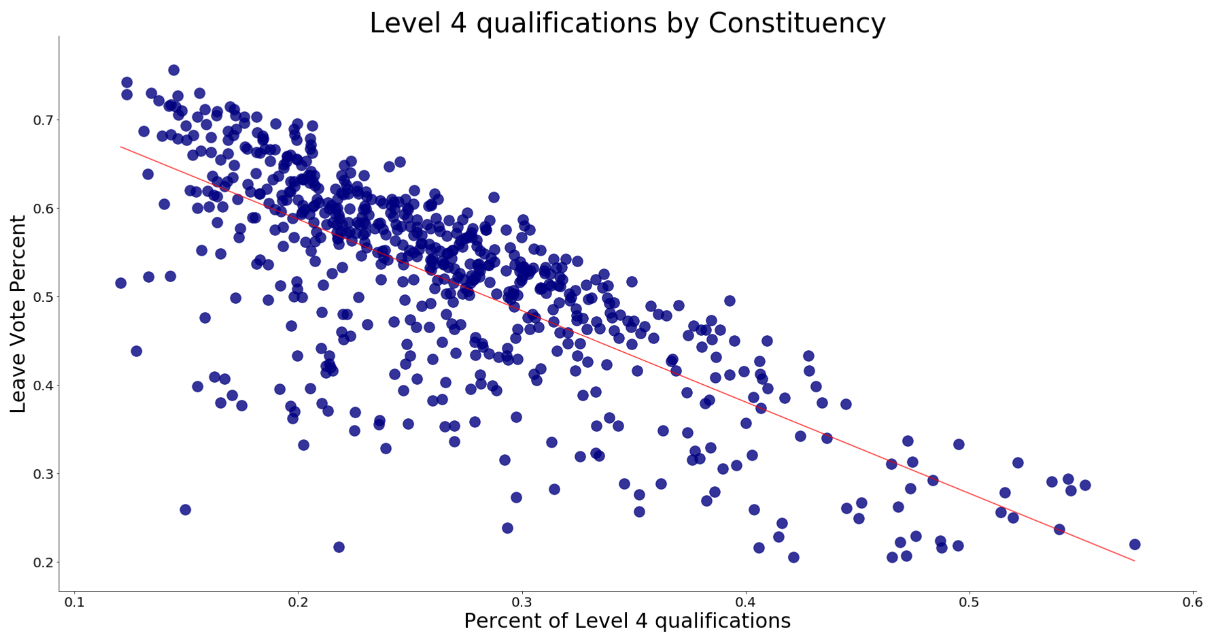
```
Out[744]: Text(0.5,0.98,'Education')
```



Looking at graphs, we see that there is a strong positive correlation. This suggests that idividuals with lower levels of education voted for Brexit. This could be because lower levels of education are linked with lower incomes.

In [745]:
```
fig, ax = plt.subplots(figsize = (30,15))

ax.scatter(masterDf['Pct_Level 4 qualifications'], masterDf['Pct_leave'
],s = 240, alpha = 0.8, color = 'navy')
ax.spines["right"].set_visible(False)

ax.spines["top"].set_visible(False)
ax.set_title("Level 4 qualifications by Constituency", fontsize = 40)
ax.set_ylabel("Leave Vote Percent", fontsize = 30)
ax.set_xlabel("Percent of Level 4 qualifications", fontsize = 30)
ax.tick_params(axis = 'both', which = 'major', labelsize = 20)


x = masterDf['Pct_Level 4 qualifications']
y = masterDf['Pct_leave']
ax.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.unique(x)), c =
"r",alpha = 0.8)
```

Out[745]:
```
[<matplotlib.lines.Line2D at 0x14c3cc9e8>]
```



In contrast, those with the highest level of education had a negative correlation. The more educated an area is the less likely it was to vote for Brexit.

Unemployment

In [746]:
```
#import and set up
employmentUrl ="https://raw.githubusercontent.com/harryb328/databootcamp
project/master/Employment_by_constituency%20.csv"
employmentDf = pd.read_csv(employmentUrl)
employmentDf = employmentDf.sort_values(by='geography', ascending=True)
employmentDf = employmentDf.set_index(['geography code'])
```

In [747]:
```
employmentDf.head()
```

Out[747]:

	geography	Working Age Pop	Economically active	Employed	Unemployed	Full-time student	Neve worke
geography code							
W07000049	Aberavon	48646	30113	26692	2335	1086	370
W07000058	Aberconwy	40443	27231	24464	1605	1162	178
S14000001	Aberdeen North	79096	55750	45268	2917	7565	355
S14000002	Aberdeen South	72437	54458	48157	1992	4309	214
S14000003	Airdrie and Shotts	64143	43731	37841	4134	1756	633

In [748]:
```
#Place percentage unemployed in master dataframe
masterDf["Pct_unemployed"] = employmentDf["Unemployed"]/employmentDf["Wo
rking Age Pop"]
```

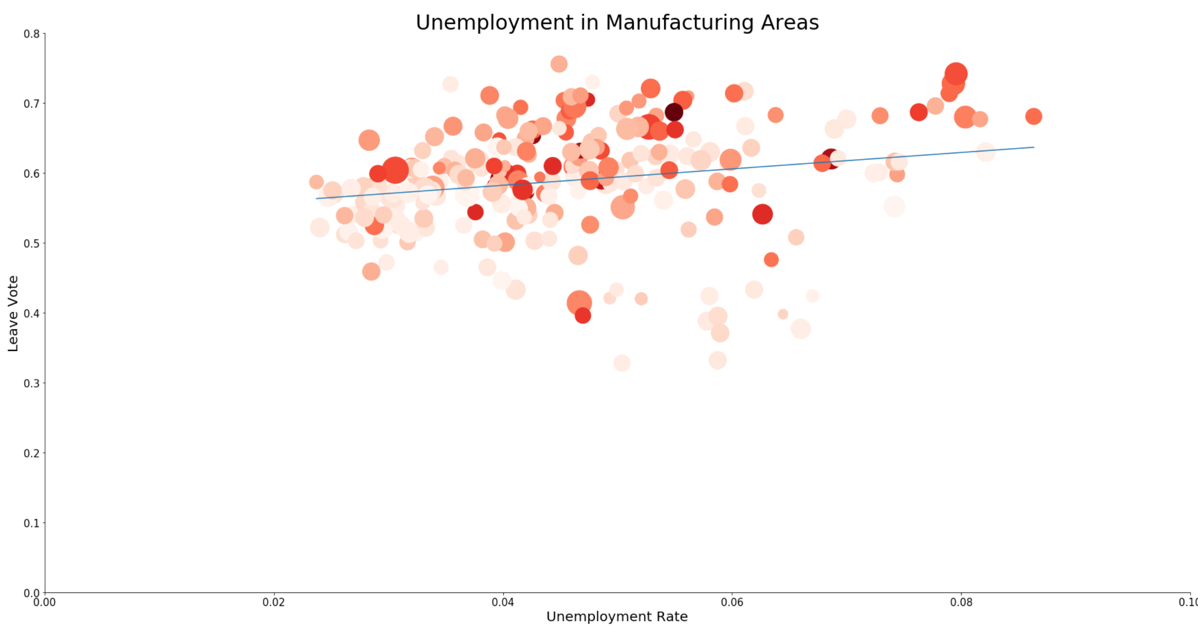
In [749]:
```
fig, ax = plt.subplots(figsize = (35,15))
color = masterDf['Pct_manufacturing']
cmap = "seismic"
artist = ax.scatter(masterDf['Pct_unemployed'], masterDf['Pct_leave'], c
 = color ,s = employmentDf['Working Age Pop']**2/8000000,alpha = 0.8, cm
ap = cmap)

ax.set_title("Unemployment", fontsize = 30)
ax.set_xlabel("Unemployment Rate", fontsize = 20)
ax.set_ylabel("Leave Vote", fontsize = 20)
ax.tick_params(axis = 'both', which = 'major', labelsize = 15)

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

cbar = fig.colorbar(artist, label = "Percentage of workers in Manufactur
ing")
```

This shows that ther was no direct link between unemployment and the brexit vote. However, it does show that areas with high manfacturing unemployment were more likely to vote for brexit than areas with high service sectir unemployment.

In [750]:
```
x = masterDf.loc[masterDf['Pct_manufacturing'] > 0.3, 'Pct_unemployed']
y = masterDf.loc[masterDf['Pct_manufacturing'] > 0.3, 'Pct_leave']
cl = masterDf.loc[masterDf['Pct_manufacturing'] > 0.3, 'Pct_manufacturin
g']
```

In [751]:
```
fig, ax = plt.subplots(figsize = (30,15))
color = cl
cmap = "Reds"
ax.scatter(x, y,c = color,s = employmentDf['Working Age Pop']**2/8000000
,alpha = 1, cmap = cmap)
ax.spines["right"].set_visible(False) # remove the top and right spines

ax.spines["top"].set_visible(False) # Same as above

ax.set_title("Unemployment in Manufacturing Areas", fontsize = 30)
ax.set_xlabel("Unemployment Rate", fontsize = 20)
ax.set_ylabel("Leave Vote", fontsize = 20)
ax.tick_params(axis = 'both', which = 'major', labelsize = 15)

ax.set_xlim(0,0.1) #
ax.set_ylim(0,0.8)


ax.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.unique(x)))
```

Out[751]: [<matplotlib.lines.Line2D at 0x14e28dba8>]



Looking solely at unemployment in areas with a high percentage of manufacturing, we see that there is a slight positive correclation. Thus, higher unemployment in these areas could have lead to more leave.

In [752]:
```
#Exclude London
x = masterDf.loc[masterDf['London'] == 0, 'Pct_unemployed']
y = masterDf.loc[masterDf['London'] == 0, 'Pct_leave']
cl = masterDf.loc[masterDf['London'] == 0, 'Pct_manufacturing']
sl = employmentDf.loc[masterDf['London'] == 0, 'Working Age Pop']
```

Unemployment (ex. London)

In [753]:
```
fig, ax = plt.subplots(figsize = (35,15))
color = cl
cmap = "seismic"
artist = ax.scatter(x, y, c = color ,s = employmentDf['Working Age Pop']
**2/8000000,alpha = 0.8, cmap = cmap)

ax.set_title("Unemployment outside of London", fontsize = 30)
ax.set_xlabel("Unemployment Rate", fontsize = 20)
ax.set_ylabel("Leave Vote", fontsize = 20)
ax.tick_params(axis = 'both', which = 'major', labelsize = 15)

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

cbar = fig.colorbar(artist, label = "Percentage of workers in Manufactur
ing")

ax.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.unique(x)))
```

Out[753]: [<matplotlib.lines.Line2D at 0x14f5e2438>]

Unemployment outside of London may have a larger effect than in London. It shows that there is a slight positive correrlation between leave votes and unemployment. Furthermore, as unemployemnt grows the dots become less concentrated.

Conclusion

The data shows that the number of immigrants in Britain did not have an affect on the vote, despite what people thought. Education levels and job sector had a much larger effect on the vote. It shows that lower socio economic areas predominantly voted for Brexit. Unemployment levels did not have a greater effect on the vote. However, outside of London there was a greater correlation.

After this analyze it seems that lower socio eonomic citizens were angered at the European Unions affect on the UK. They may have perceived immigration to be the problem even though it wasn't.