cs109a_finalproject_submission

December 7, 2017

0.1 Packages used that are not included in Jupyter Notebook.

Fuzzywuzzy-- string matching using Levenshtein Distance to calculate the differences between strings

https://pypi.python.org/pypi/fuzzywuzzy

Geopy-- locates the coordinates of addresses, cities, countries, and landmarks across the globe using third-party geocoders and other data sources

https://pypi.python.org/pypi/geopy

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import pickle
        import seaborn as sns
        import requests
        from bs4 import BeautifulSoup
        from fuzzywuzzy import fuzz
        import cartopy.crs as ccrs
        import matplotlib.pyplot as plt
        import matplotlib.patches as mpatches
        import matplotlib.pyplot as plt
        import shapely.geometry as sgeom
        import cartopy.io.shapereader as shpreader
        import cartopy
        import pickle
        from geopy.geocoders import Nominatim
        import math
        import plotly.plotly as py
        import plotly


        from sklearn.preprocessing import MinMaxScaler
        from sklearn.linear_model import LassoCV
        from sklearn.linear_model import RidgeCV
        from sklearn.linear_model import LinearRegression
        from sklearn.metrics import r2_score
        from sklearn.preprocessing import StandardScaler
        from sklearn.ensemble import RandomForestRegressor
```

```
        from sklearn.preprocessing import PolynomialFeatures
        from sklearn.decomposition import PCA
        from sklearn.ensemble import RandomForestRegressor
        % matplotlib inline
```

```
/Users/jeanettejin/anaconda/lib/python3.6/site-packages/fuzzywuzzy/fuzz.py:35: UserWarning: Usin
  warnings.warn('Using slow pure-python SequenceMatcher. Install python-Levenshtein to remove th
```

1 Data Collection

1.1 FBI Data

Here, we scrape from the FBI webpage, getting the hyperlinks for each year, and then we naviagate to violent crimes and murders, getting the URL for each year's MSA table.

```
In [2]: # Code that scrapes data from each webpage for each year

        ## for each year
        req = requests.get("https://ucr.fbi.gov/ucr-publications")
        page = req.text
        soup = BeautifulSoup(page, 'html.parser')

        # scrape links from main website
        links = []
        span = soup.find_all('span', class_= 'castle-body')[4]
        a = span.find_all('a')

        for link in a:
            links.append(link['href'])
        links = links[0:11]
        links

        # redefine link for 09
        links[7] = 'https://www2.fbi.gov/ucr/cius2009/index.html'

        ## going to violent crimes
        violence = []

        for link in links:
            req = requests.get(link)
            page = req.text
            soup = BeautifulSoup(page, 'html.parser')
            href = soup.find_all('a', href = True, text = 'Violent Crime')[0]['href']
            if 'https' in href:
                violence.append(href)

            else:
```

```
        if 'index.html' in link:
            link = link.replace('index.html', '')
            violence.append(link + href)
        else:
            violence.append(link + '/' + href)

## going to MSA table
table = []
for v in violence:
    page = requests.get(v).text
    soup = BeautifulSoup(page, 'html.parser')
    a = soup.find_all('a', href = True)
    for i in a:
        if 'Statistical Areas' in i.text:
            if 'https' in i['href']:
                table.append(i['href'])
            else:
                if 'violent_crime' in v:
                    v = v.replace('offenses/violent_crime/index.html','')
                    table.append(v + 'data/table_06.html')
table
```

```
Out[2]: ['https://ucr.fbi.gov/crime-in-the-u.s/2016/crime-in-the-u.s.-2016/tables/table-4',
 'https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/tables/table-6',
 'https://ucr.fbi.gov/crime-in-the-u.s/2014/crime-in-the-u.s.-2014/tables/table-6',
 'https://ucr.fbi.gov/crime-in-the-u.s/2013/crime-in-the-u.s.-2013/tables/6tabledatadecp
 'https://ucr.fbi.gov/crime-in-the-u.s/2012/crime-in-the-u.s.-2012/tables/6tabledatadecp
 'https://ucr.fbi.gov/crime-in-the-u.s/2011/crime-in-the-u.s.-2011/tables/table-6',
 'https://ucr.fbi.gov/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/tables/table-6',
 'https://www2.fbi.gov/ucr/cius2009/data/table_06.html',
 'http://www2.fbi.gov/ucr/cius2008/data/table_06.html',
 'http://www2.fbi.gov/ucr/cius2007/data/table_06.html',
 'http://www2.fbi.gov/ucr/cius2006/data/table_06.html']
```

We define a function to parse the tables for each year. This function was adapted from http://srome.github.io/Parsing-HTML-Tables-in-Python-with-BeautifulSoup-and-pandas/, but makes many changes to td/th tag checks, dataframe indexing, changes to find the dimensions of the dataframe, and changes to float/int recast.

```
In [3]: # Adapted from http://srome.github.io/Parsing-HTML-Tables-in-Python-with-BeautifulSoup-a
        # changes to td/th checks
        # changes to dataframe indexing
        # changes to how we find dim of dataframe
        # changes to float/int recast


        def parse_table(table):
                n_columns = 0
```

```python
n_rows = 0
column_names = []

# Find number of rows and columns
# we also find the column titles if we can
colidx = 0
rows = table.find_all('tr')
n_rows = len(rows)-1
td_tags = rows[0].find_all('td')
th_tags = rows[0].find_all('th')
n_columns = len(th_tags) + len(td_tags)
for th in th_tags:
    column_names.append(th.get_text().strip())

# Safeguard on Column Titles
if len(column_names) > 0 and len(column_names) != n_columns:
    raise Exception("Column titles do not match the number of columns")

columns = column_names if len(column_names) > 0 else range(0,n_columns)
df = pd.DataFrame(columns = columns,
                  index= range(0,n_rows))
row_marker = 0

# find all rows and iterate over each row (skip first row- those are the columns
for row in rows[1:]:
    # check if 2 th's (means at Abilene)
    numb_cols = len(row.find_all('td')) + len(row.find_all('th'))
    if numb_cols == n_columns:
        column_marker = 0
    else:
        df.iat[row_marker,0] = ''
        column_marker = 1

# find each column header (there are 2 column headers and 10 td's)
    colheads = row.find_all('th')
    if row_marker == 0:
        print(df.iat[0,0])
    for colhead in colheads:
        df.iat[row_marker,column_marker] = colhead.get_text().strip()
        column_marker+=1

# find the 10 td's and append to dataframe
    columns = row.find_all('td')
    for column in columns:
        df.iat[row_marker,column_marker] = column.get_text().strip()
        column_marker += 1
    if len(columns) > 0:
        row_marker += 1
```

```
        return df
```

We use the function defined above to scape all elements in the table and store them in a dictionary of dataframes with keys = year

```
In [4]: # store the tables in a dictionary with key = year
        yeartbl = {}
        year = 2016
        for t in table:
            page = requests.get(t).text
            soup = BeautifulSoup(page, 'lxml')
            i = 0
            # pick the first table with many rows
            while len(soup.find_all('table')[i].find_all('tr')) < 200:
                i += 1
            a = soup.find_all('table')[i]
            tempdf = parse_table(a)
            yeartbl[year] = tempdf
            year = year - 1
```

```
nan
nan
nan
nan
nan
nan
nan
nan
nan
nan
nan
```

An example:

```
In [5]: yeartbl[2006].head()
```

```
Out[5]:   Metropolitan Statistical Area  \
        0           Abilene, TX M.S.A.1
        1
        2
        3
        4

                               Counties/principal cities Population Violent crime  \
        0                                                   162,776
        1  Includes Callahan,1 Jones, and Taylor Counties
        2                                    City of Abilene    118,009           554
```

```
3                    Total area actually reporting     100.0%           638
4                     Rate per 100,000 inhabitants                    391.9

  Murder and nonnegligent manslaughter Forcible rape Robbery  \
0
1
2                                    5            67     107
3                                    6            75     109
4                                  3.7          46.1    67.0

  Aggravated assault Property crime Burglary Larceny-theft Motor vehicle theft
0
1
2                375          5,045    1,282         3,460                 303
3                448          5,741    1,531         3,852                 358
4              275.2        3,526.9    940.6       2,366.4               219.9
```

Changing column names:

```
In [6]: # replace old column names with easier to use
        new_col_names = ['MSA', 'Counties', 'Population', 'Violent_Crime', 'Murder', 'Rape', 'Ro
            'Vehicle_Theft']

        i = 2016

        while i != 2005:
            yeartbl[i].columns = new_col_names
            i = i - 1
```

We are only interested in the MSA and its murder counts for each year. For each table in our dictionary we find this information and put them into another dictionary of dataframe with key = year

```
In [7]: # since we only care about murder at the moment lets change the type to numeric
        i = 2016

        murder_stats = {}
        while i != 2005:
            temp = yeartbl[i]

            # remove commas to change type
            temp['Murder'] = temp['Murder'].str.replace(",", "")
            temp['Murder'] = pd.to_numeric(temp['Murder'])
            temp['MSA'][temp['MSA'] == ''] = np.NaN
            temp['MSA'] = temp['MSA'].fillna(method = 'ffill')
            murders = temp[temp["Counties"].str.contains("Total area actually reporting")][['MSA
            murder_stats[i] = murders
            i = i - 1
```

An example:

```
In [8]: murder_stats[2006].head()
```

```
Out[8]:                                  MSA  Murder
        3                Abilene, TX M.S.A.1     6.0
        8                  Albany, GA M.S.A.    11.0
        16  Albany-Schenectady-Troy, NY M.S.A.  18.0
        21            Albuquerque, NM M.S.A.    72.0
        27             Alexandria, LA M.S.A.    10.0
```

```
In [9]: # lengths of each dataframe
        for i in range(2006,2017):
            print(len(murder_stats[i]))
```

```
357
364
357
378
368
376
389
384
377
377
386
```

1.2 Census Data

We download csv files of for year 2006 - 2016 for the following features take from the Census Data by each MSA

S0101: Age and Sex S1201: Marital Status S1501: Educational Attainment S1701: Poverty Status in the Past 12 Months S1903: Median income in the past 12 months B02001: Race B01003: Total Population

Below we define some functions to help us with the cleaning process:

```
In [10]: # makes the df column names the first row
         def rename(df):
             header = df.iloc[0]
             df = df.iloc[1:]
             df = df.rename(columns = header)
             return df

         # names of the csv files
         def makefile_names(code, some_list):
             for i in list(range(6, 17)):
                     num = "%02d" % (i,)
```

```
            if i == 6:
                some_list.append('Census Data/ACS_06_EST_' + code + '_with_ann.csv')
            else:
                some_list.append('Census Data/ACS_' + num  + '_1YR_' + code + '_with_an
        return some_list
```

```
In [11]: # the codes of each feature
         codes = ['S0101', 'S1201', 'S1501', 'S1701', 'S1903', 'B02001','B01003']

         filenames = {}

         names = ['age_sex', 'marital', 'education', 'poverty', 'income', 'race', 'population']

         for i in range(0, len(names)):
             list_name = []
             filenames[names[i]] = makefile_names(codes[i], list_name)
```

1.2.1 Feature: Population

We use the first feature population to put each MSA into a dictionary with key = unique identifier. For each year we iterate through the dataframe's MSA and check to see if it exists within our dictionary. If not, we add it to our dictionary. This ensures that we will have nan values for MSAs that do not appear throughout all the years.

```
In [12]: dict_pop_year = {}

         # make a dict of dict with each being {msa_code: population_year}
         for i in range(0, len(filenames['population'])):

             # load as df
             df_pop_year = pd.read_csv(filenames['population'][i], encoding = "ISO-8859-1")
             print(len(df_pop_year))

             # clean
             df_pop_year = rename(df_pop_year)
             df_pop_year[['Id2']] = df_pop_year[['Id2']].astype(int)
             df_pop_year['Geography'] = df_pop_year['Geography'].str.replace(' Metro Area', '')

             # make a dict of id and name of msa
             if i == 0:
                 msa_dict = dict(zip(df_pop_year['Id2'], df_pop_year['Geography']))

             else:
                 for code,name in zip(df_pop_year['Id2'], df_pop_year['Geography']):
                     msa_dict.setdefault(code, name)

             dict_pop = dict(zip(df_pop_year['Id2'], df_pop_year['Estimate; Total']))
```

```
        dict_pop_year['pop' + "_%02d" % (i + 6,)] = dict_pop

# printed are the number of unique msa's per year!
```

```
368
370
370
375
375
375
375
389
389
389
390
```

We use the dictionary with key = Unique idenitifier and value the names of the MSA and create a df with all of the populations for each year.

In [13]:
```
# make dataframe using dict keys
msa_df = pd.DataFrame.from_dict(msa_dict, orient = 'index')
msa_df.columns = ['msa_name']

# add to dict using keys
for key in dict_pop_year:
    msa_df[key] = pd.Series(dict_pop_year[key])

# show
msa_df.head()
```

Out[13]:
```
                                 msa_name  pop_06  pop_07  pop_08  pop_09  \
10180                         Abilene, TX  158548  159439  160012  160266
10380  Aguadilla-Isabela-San Sebastián, PR  336502  335201  339193  342495
10420                           Akron, OH  700943  699356  698553  699935
10500                          Albany, GA  165062  162767  163074  164238
10580          Albany-Schenectady-Troy, NY  850957  853358  853919  857592

       pop_10  pop_11  pop_12  pop_13  pop_14  pop_15  pop_16
10180  164941  165858  167800  168144  166900  168922  170860
10380  305988  304633  304727  327847  322079  313209  309764
10420  702951  701456  702262  705686  703825  704243  702221
10500  162659  161617  155019  156277  152596  156997  152506
10580  870832  871478  874646  877905  880167  881830  881839
```

We do this for every feature using the unique identifier to add features to our dataframe

1.2.2 Feature: Sex and Year

```
In [14]: dict_agesex_year = {}

         for i in range(0, len(filenames['age_sex'])):

             # load and clean
             df_agesex_year = pd.read_csv(filenames['age_sex'][i], encoding = 'ISO-8859-1')
             df_agesex_year = rename(df_agesex_year)

             # get columns names
             gender_columns = ['Male; Estimate; Total population', 'Female; Estimate; Total popu
             age_columns = [x for x in df_agesex_year.columns.values.tolist() if x.startswith("T
             if len(age_columns) == 0:
                 age_columns = df_agesex_year.columns[df_agesex_year.columns.str.contains('Total
             int_columns = gender_columns + ['Total; Estimate; Total population', 'Id2']

             # change type
             df_agesex_year[int_columns] = df_agesex_year[int_columns].astype(int)
             df_agesex_year[age_columns] = df_agesex_year[age_columns].astype(float)

             # make a column for the percent of male and females in each msa
             df_agesex_year['Percent_male'] = df_agesex_year[gender_columns[0]] / df_agesex_year
             df_agesex_year['Percent_female'] = df_agesex_year[gender_columns[1]] / df_agesex_ye

             # select columns
             add_columns_agesex = ['Percent_male', 'Percent_female'] + age_columns

             # fill dict
             for feature in add_columns_agesex:
                 dict_agesex = dict(zip(df_agesex_year['Id2'], df_agesex_year[feature]))
                 dict_agesex_year[feature + "_%02d" % (i + 6,) ] = dict_agesex

         # add to dataframe
         for key in dict_agesex_year:
              msa_df[key] = pd.Series(dict_agesex_year[key])

         # rename and show
         msa_df.columns = msa_df.columns.str.replace('Total; Estimate; ', '')
         msa_df.columns = msa_df.columns.str.replace('Total population - ', '')
         msa_df.head()
```

```
Out[14]:                                 msa_name  pop_06  pop_07  pop_08  pop_09  \
         10180                        Abilene, TX  158548  159439  160012  160266
         10380  Aguadilla-Isabela-San Sebastián, PR  336502  335201  339193  342495
         10420                          Akron, OH  700943  699356  698553  699935
         10500                         Albany, GA  165062  162767  163074  164238
         10580          Albany-Schenectady-Troy, NY  850957  853358  853919  857592
```

```
       pop_10  pop_11  pop_12  pop_13  pop_14              ...                \
10180  164941  165858  167800  168144  166900              ...
10380  305988  304633  304727  327847  322079              ...
10420  702951  701456  702262  705686  703825              ...
10500  162659  161617  155019  156277  152596              ...
10580  870832  871478  874646  877905  880167              ...

      AGE - 40 to 44 years_16 AGE - 45 to 49 years_16  \
10180                     4.4                     5.3
10380                     6.0                     6.4
10420                     5.5                     6.5
10500                     5.4                     5.6
10580                     5.6                     6.7

       AGE - 50 to 54 years_16  AGE - 55 to 59 years_16  \
10180                      6.2                      5.2
10380                      6.5                      6.5
10420                      7.3                      7.4
10500                      6.1                      6.6
10580                      7.3                      7.5

       AGE - 60 to 64 years_16  AGE - 65 to 69 years_16  \
10180                      5.9                      5.3
10380                      6.6                      6.4
10420                      6.9                      5.7
10500                      6.6                      5.6
10580                      6.3                      5.6

       AGE - 70 to 74 years_16  AGE - 75 to 79 years_16  \
10180                      3.3                      2.7
10380                      5.0                      3.5
10420                      3.9                      2.8
10500                      3.3                      2.4
10580                      3.8                      2.2

       AGE - 80 to 84 years_16  AGE - 85 years and over_16
10180                      2.1                         1.8
10380                      2.1                         1.8
10420                      1.9                         2.4
10500                      2.0                         1.5
10580                      2.0                         2.6

[5 rows x 232 columns]
```

1.2.3 Feature: Marriage Status

In [15]:
```
dict_marital_year = {}
```

```
for i in range(0, len(filenames['marital'])):

    # load and clean
    df_marital = pd.read_csv(filenames['marital'][i], encoding='cp1252')
    df_marital = rename(df_marital)
    df_marital = df_marital.loc[:,~df_marital.columns.duplicated()]
    df_marital = df_marital.replace("N", np.nan)


    # features
    status_columns = ['Now married (except separated); Estimate; Population 15 years an

    # change type
    df_marital[status_columns] = df_marital[status_columns].astype(float)
    df_marital['Id2'] = df_marital['Id2'].astype(float)

    # fill dict with dicts
    for feature in status_columns:
            dict_marital = dict(zip(df_marital['Id2'], df_marital[feature]))
            dict_marital_year[feature + "_%02d" % (i + 6,) ] = dict_marital



# add to df
for key in dict_marital_year:
    msa_df[key] = pd.Series(dict_marital_year[key])

# clean column names and show
msa_df.columns = msa_df.columns.str.replace('; Estimate; Population 15 years and over',
msa_df.columns = msa_df.columns.str.replace('except separated', '')
msa_df.head()
```

Out[15]:

```
                                  msa_name  pop_06  pop_07  pop_08  pop_09  \
10180                          Abilene, TX  158548  159439  160012  160266
10380  Aguadilla-Isabela-San Sebastián, PR  336502  335201  339193  342495
10420                            Akron, OH  700943  699356  698553  699935
10500                           Albany, GA  165062  162767  163074  164238
10580          Albany-Schenectady-Troy, NY  850957  853358  853919  857592

       pop_10  pop_11  pop_12  pop_13  pop_14        ...         \
10180  164941  165858  167800  168144  166900        ...
10380  305988  304633  304727  327847  322079        ...
10420  702951  701456  702262  705686  703825        ...
10500  162659  161617  155019  156277  152596        ...
10580  870832  871478  874646  877905  880167        ...

      Now married ()_15 Widowed_15  Divorced_15  Separated_15  \
10180              45.4        6.6         12.0           3.3
```

```
10380              41.7        7.1          12.0            3.8
10420              46.7        6.3          11.9            1.3
10500              39.4        7.8          12.6            5.2
10580              45.1        5.9           9.8            1.9

       Never married_15  Now married ()_16  Widowed_16  Divorced_16  \
10180              32.8               46.8         5.5         10.9
10380              35.3               39.5         7.2         12.6
10420              33.8               46.9         5.9         11.5
10500              35.0               39.8         6.8         12.0
10580              37.2               44.2         6.5         10.2

       Separated_16  Never married_16
10180           2.5              34.2
10380           3.1              37.7
10420           1.6              34.1
10500           3.3              38.2
10580           2.2              36.9

[5 rows x 287 columns]
```

1.2.4 Feature: Education

In [16]:
```python
dict_education_year = {}

for i in range(0, len(filenames['education'])):

    # load and clean
    df_education = pd.read_csv(filenames['education'][i], encoding='cp1252')
    df_education = rename(df_education)


    # features (gov naming conventions suck)
    if i < 4:
        education_columns = ['Total; Estimate; Population 25 years and over - Percent h

    if 4 <= i <= 8:
        education_columns = ['Total; Estimate; Percent high school graduate or higher',

    if i > 8:
        education_columns = ['Percent; Estimate; Percent high school graduate or higher

    # change datatype
    df_education[education_columns] = df_education[education_columns].astype(float)
    df_education['Id2'] = df_education['Id2'].astype(int)

    # create dict of dicts
    for feature in education_columns:
```

```
        dict_education = dict(zip(df_education['Id2'], df_education[feature]))
        dict_education_year[feature + "_%02d" % (i + 6,) ] = dict_education

# add to dataframe
for key in dict_education_year:
    msa_df[key] = pd.Series(dict_education_year[key])

# clean column names and show
msa_df.columns = msa_df.columns.str.replace('Total; Estimate;', '')
msa_df.columns = msa_df.columns.str.replace('Percent; Estimate;', '')
msa_df.columns = msa_df.columns.str.replace('Population 25 years and over - ', '')
msa_df.head()
```

Out[16]:

```
                                  msa_name  pop_06  pop_07  pop_08  pop_09  \
10180                          Abilene, TX  158548  159439  160012  160266
10380  Aguadilla-Isabela-San Sebastián, PR  336502  335201  339193  342495
10420                            Akron, OH  700943  699356  698553  699935
10500                           Albany, GA  165062  162767  163074  164238
10580         Albany-Schenectady-Troy, NY  850957  853358  853919  857592

       pop_10  pop_11  pop_12  pop_13  pop_14  \
10180  164941  165858  167800  168144  166900
10380  305988  304633  304727  327847  322079
10420  702951  701456  702262  705686  703825
10500  162659  161617  155019  156277  152596
10580  870832  871478  874646  877905  880167

                        ...                        \
10180                   ...
10380                   ...
10420                   ...
10500                   ...
10580                   ...

       Percent high school graduate or higher_12  \
10180                                       83.5
10380                                       66.0
10420                                       90.6
10500                                       79.9
10580                                       92.0

       Percent bachelor's degree or higher_12  \
10180                                    21.2
10380                                    20.5
10420                                    28.4
10500                                    18.4
10580                                    34.1
```

```
       Percent high school graduate or higher_13  \
10180                                       83.8
10380                                       63.3
10420                                       91.1
10500                                       80.1
10580                                       92.1

       Percent bachelor's degree or higher_13  \
10180                                    22.1
10380                                    18.2
10420                                    29.7
10500                                    16.4
10580                                    34.3

       Percent high school graduate or higher_14  \
10180                                       86.1
10380                                       67.6
10420                                       91.1
10500                                       81.5
10580                                       92.5

       Percent bachelor's degree or higher_14  \
10180                                    21.6
10380                                    19.8
10420                                    29.9
10500                                    19.0
10580                                    35.4

       Percent high school graduate or higher_15  \
10180                                       87.7
10380                                       68.7
10420                                       91.5
10500                                       82.3
10580                                       92.2

       Percent bachelor's degree or higher_15  \
10180                                    20.7
10380                                    20.4
10420                                    30.1
10500                                    21.1
10580                                    35.3

       Percent high school graduate or higher_16  \
10180                                       86.7
10380                                       67.3
10420                                       91.8
10500                                       84.8
10580                                       91.6
```

```
       Percent bachelor's degree or higher_16
10180                                    20.4
10380                                    17.8
10420                                    31.0
10500                                    18.6
10580                                    37.4

[5 rows x 309 columns]
```

1.2.5 Feature Poverty

In [17]:
```python
dict_poverty_year = {}

for i in range(0, len(filenames['poverty'])):

    # load and clean
    df_poverty = pd.read_csv(filenames['poverty'][i], encoding='cp1252')
    df_poverty = rename(df_poverty)

    # find column name and set (a difference of a space between percent and below...)
    a = 'Percent  below poverty level; Estimate; Population for whom poverty status is
    b = 'Percent below poverty level; Estimate; Population for whom poverty status is d

    if a in df_poverty:
        poverty_column = a

    if b in df_poverty:
        poverty_column = b

    # change dtype
    df_poverty[poverty_column] = df_poverty[poverty_column].astype(float)
    df_poverty['Id2'] = df_poverty['Id2'].astype(int)

    # make a dict of dicts
    dict_poverty = dict(zip(df_poverty['Id2'], df_poverty[poverty_column]))
    dict_poverty_year['poverty' + "_%02d" % (i + 6,) ] = dict_poverty

# add each dict in dict to msa df
for key in dict_poverty_year:
    msa_df[key] = pd.Series(dict_poverty_year[key])

msa_df.head()
```

Out[17]:
```
                                 msa_name  pop_06  pop_07  pop_08  pop_09  \
10180                         Abilene, TX  158548  159439  160012  160266
10380  Aguadilla-Isabela-San Sebastián, PR  336502  335201  339193  342495
10420                           Akron, OH  700943  699356  698553  699935
```

```
10500                           Albany, GA  165062  162767  163074  164238
10580          Albany-Schenectady-Troy, NY  850957  853358  853919  857592

       pop_10  pop_11  pop_12  pop_13  pop_14     ...     poverty_07  \
10180  164941  165858  167800  168144  166900     ...           15.1
10380  305988  304633  304727  327847  322079     ...           57.6
10420  702951  701456  702262  705686  703825     ...           13.4
10500  162659  161617  155019  156277  152596     ...           21.5
10580  870832  871478  874646  877905  880167     ...           10.1

      poverty_08  poverty_09  poverty_10  poverty_11  poverty_12  poverty_13  \
10180       16.1        14.5        18.0        16.9        20.5        16.8
10380       54.5        55.4        53.8        54.0        53.7        53.8
10420       12.1        14.7        15.5        16.6        15.7        15.4
10500       23.3        23.2        27.7        28.4        26.9        24.9
10580       10.5         9.9        11.5        11.5        11.0        12.5

       poverty_14  poverty_15  poverty_16
10180        16.5        13.9        17.2
10380        53.4        53.7        54.1
10420        13.3        14.2        13.8
10500        25.3        24.6        25.0
10580        11.7        10.2         9.9

[5 rows x 320 columns]
```

1.2.6 Feature: Income

In [18]:
```
dict_income_year = {}

for i in range(0, len(filenames['income'])):

    # load and clean
    df_income = pd.read_csv(filenames['income'][i], encoding = 'cp1252')
    df_income = rename(df_income)

    # get column name
    income_column = [x for x in df_income.columns.values.tolist() if x.startswith('Medi

    # dtypes
    df_income[income_column] = df_income[income_column].astype(float)
    df_income['Id2'] = df_income['Id2'].astype(int)

    # dict of dicts
    dict_income = dict(zip(df_income['Id2'], df_income[income_column]))
    dict_income_year['median_income' + "_%02d" % (i + 6,) ] = dict_income

# add each dict in dict to msa df
```

```
    for key in dict_income_year:
        msa_df[key] = pd.Series(dict_income_year[key])

    msa_df.head()
```

Out[18]:

```
                                   msa_name  pop_06  pop_07  pop_08  pop_09  \
10180                           Abilene, TX  158548  159439  160012  160266
10380  Aguadilla-Isabela-San Sebastián, PR  336502  335201  339193  342495
10420                             Akron, OH  700943  699356  698553  699935
10500                            Albany, GA  165062  162767  163074  164238
10580          Albany-Schenectady-Troy, NY  850957  853358  853919  857592

       pop_10  pop_11  pop_12  pop_13  pop_14         ...          \
10180  164941  165858  167800  168144  166900         ...
10380  305988  304633  304727  327847  322079         ...
10420  702951  701456  702262  705686  703825         ...
10500  162659  161617  155019  156277  152596         ...
10580  870832  871478  874646  877905  880167         ...

      median_income_07 median_income_08  median_income_09  median_income_10  \
10180          39369.0          41961.0           42931.0           40630.0
10380          12139.0          13152.0           13470.0           14313.0
10420          47898.0          50036.0           47482.0           46521.0
10500          36402.0          38989.0           36218.0           34002.0
10580          55129.0          58765.0           57677.0           55796.0

       median_income_11  median_income_12  median_income_13  median_income_14  \
10180           40659.0           43407.0           44149.0           44303.0
10380           14951.0           15339.0           15323.0           15886.0
10420           47032.0           49731.0           49984.0           50538.0
10500           32775.0           34469.0           34756.0           39071.0
10580           58617.0           60625.0           59626.0           62265.0

       median_income_15  median_income_16
10180           47420.0           48016.0
10380           14485.0           14546.0
10420           51580.0           51598.0
10500           40143.0           40667.0
10580           63080.0           65855.0

[5 rows x 331 columns]
```

1.2.7 Feature Race

In [19]:

```
dict_race_year = {}

    for i in range(0, len(filenames['race'])):
```

```
    # load and clean
    df_race = pd.read_csv(filenames['race'][i], encoding= 'cp1252')
    df_race = rename(df_race)

    # finding column names of interest
    df_race.columns = df_race.columns.str.replace('Estimate;', '')
    df_race.rename(columns={" Total:" : 'TOTAL'}, inplace = True)
    df_race = df_race[df_race.columns.drop(list(df_race.filter(regex='Margin')))]
    column_divide = df_race.columns.tolist()[3 :-2]
    column_divide.append('Id2')

    # change datatype
    df_race[column_divide] = df_race[column_divide].astype(int)

    names = []

    # getting percentages
    for feature in column_divide[1:-1]:
        df_race[feature + '_Percent'] = df_race[feature] / df_race['TOTAL']
        names.append(feature + '_Percent')

    # dict of dicts
    for feature in names:
        dict_race = dict(zip(df_race['Id2'], df_race[feature]))
        dict_race_year[feature + "_%02d" % (i + 6,)] = dict_race

# add each dict in dict to msa df
for key in dict_race_year:
    msa_df[key] = pd.Series(dict_race_year[key])

# cleaning column names
msa_df.columns = msa_df.columns.str.replace("Total: - ", '')
msa_df.columns = msa_df.columns.str.replace('; ', '')
msa_df = msa_df.rename(columns=lambda x: x.strip())
msa_df.columns = msa_df.columns.str.replace(r"\s+\(.*\)","")

#
msa_df.head()
```

Out[19]:

```
                                 msa_name  pop_06  pop_07  pop_08  pop_09  \
10180                         Abilene, TX  158548  159439  160012  160266
10380  Aguadilla-Isabela-San Sebastián, PR  336502  335201  339193  342495
10420                            Akron, OH  700943  699356  698553  699935
10500                           Albany, GA  165062  162767  163074  164238
10580         Albany-Schenectady-Troy, NY  850957  853358  853919  857592

       pop_10  pop_11  pop_12  pop_13  pop_14              ...                \
10180  164941  165858  167800  168144  166900              ...
```

```
10380  305988  304633  304727  327847  322079                ...
10420  702951  701456  702262  705686  703825                ...
10500  162659  161617  155019  156277  152596                ...
10580  870832  871478  874646  877905  880167                ...

      Native Hawaiian and Other Pacific Islander alone_Percent_15  \
10180                                           0.000000
10380                                           0.000000
10420                                           0.000284
10500                                           0.000025
10580                                           0.000442

      Some other race alone_Percent_15  Two or more races:_Percent_15  \
10180                         0.096624                       0.033951
10380                         0.177460                       0.044009
10420                         0.003466                       0.029231
10500                         0.001917                       0.017504
10580                         0.013795                       0.032402

       White alone_Percent_16  Black or African American alone_Percent_16  \
10180                0.781371                                     0.082559
10380                0.704982                                     0.034152
10420                0.819179                                     0.120844
10500                0.421472                                     0.539284
10580                0.827320                                     0.075000

       American Indian and Alaska Native alone_Percent_16  \
10180                                           0.007433
10380                                           0.000588
10420                                           0.000964
10500                                           0.001692
10580                                           0.002774

       Asian alone_Percent_16  \
10180                0.020701
10380                0.000000
10420                0.028414
10500                0.009882
10580                0.043951

       Native Hawaiian and Other Pacific Islander alone_Percent_16  \
10180                                           0.000047
10380                                           0.000165
10420                                           0.000212
10500                                           0.000734
10580                                           0.000352

       Some other race alone_Percent_16  Two or more races:_Percent_16
```

```
10180                              0.078637                              0.029252
10380                              0.226595                              0.033519
10420                              0.002700                              0.027686
10500                              0.010065                              0.016871
10580                              0.017621                              0.032982

[5 rows x 408 columns]
```

Now that we have all of the Census data as one dataframe, we can split them by year. We do this below, creating a dictionary of dataframes with key = year.

```
In [20]: dict_df_year = {}

         for i in range(0, 11):
             num = "_%02d" % (i + 6,)
             filter_col = [col for col in msa_df if col.endswith(num)]
             filter_col.append('msa_name')

             dict_df_year[2006 + i] = msa_df[filter_col]
```

An example:

```
In [21]: dict_df_year[2006].head()

Out[21]:        pop_06  Percent_male_06  Percent_female_06  AGE - Under 5 years_06  \
         10180  158548         0.497717           0.502283                     7.2
         10380  336502         0.495349           0.504651                     6.2
         10420  700943         0.481664           0.518336                     5.9
         10500  165062         0.476015           0.523985                     7.8
         10580  850957         0.485577           0.514423                     5.4

                AGE - 5 to 9 years_06  AGE - 10 to 14 years_06  \
         10180                    6.4                      7.3
         10380                    6.9                      8.0
         10420                    6.3                      6.9
         10500                    7.7                      7.3
         10580                    5.9                      6.3

                AGE - 15 to 19 years_06  AGE - 20 to 24 years_06  \
         10180                      8.3                      8.7
         10380                      7.7                      7.0
         10420                      7.2                      7.2
         10500                     10.0                      6.0
         10580                      7.6                      7.4

                AGE - 25 to 29 years_06  AGE - 30 to 34 years_06  \
         10180                      6.8                      6.2
         10380                      7.0                      7.0
         10420                      6.3                      5.9
```

```
10500                    6.3                     6.0
10580                    6.8                     6.1

                 ...                   poverty_06  median_income_06  \
10180            ...                         15.8           39784.0
10380            ...                         57.0           11717.0
10420            ...                         12.7           44507.0
10500            ...                         22.8           35515.0
10580            ...                          9.8           53202.0

       White alone_Percent_06  Black or African American alone_Percent_06  \
10180                0.741838                                    0.068295
10380                0.896527                                    0.019961
10420                0.844866                                    0.116880
10500                0.485957                                    0.494136
10580                0.867237                                    0.070216

       American Indian and Alaska Native alone_Percent_06  \
10180                                           0.003570
10380                                           0.003123
10420                                           0.002129
10500                                           0.001557
10580                                           0.002378

       Asian alone_Percent_06  \
10180                0.014292
10380                0.000758
10420                0.017715
10500                0.006355
10580                0.030761

       Native Hawaiian and Other Pacific Islander alone_Percent_06  \
10180                                           0.000000
10380                                           0.000000
10420                                           0.000564
10500                                           0.000000
10580                                           0.000159

       Some other race alone_Percent_06  Two or more races:_Percent_06  \
10180                          0.148264                       0.023740
10380                          0.058686                       0.020945
10420                          0.006270                       0.011577
10500                          0.003453                       0.008542
10580                          0.014440                       0.014809

                                msa_name
10180                        Abilene, TX
10380  Aguadilla-Isabela-San Sebastián, PR
```

```
10420                              Akron, OH
10500                             Albany, GA
10580            Albany-Schenectady-Troy, NY

[5 rows x 38 columns]
```

2 Cleaning and Merging

Now we need to merge the FBI data with the Census data. We find that the FBI data uses different naming conventions from the Census Data, so we need to match each FBI df's MSA name with the Census df's MSA name, replacing the FBI names when we find a match. Below we define a few functions to help us do this. Our match_name function checks to see how similar a two MSA names are using the fuzzywuzzy package. We use a combination of scoring to return the best match.

```
In [22]: # functions for splitting, cleaning, and matching names

         # cleaning the names
         def clean_split_names(some_list):
             split_list = []
             for i in some_list:
                 split_list.append(i.split(' '))
             for i in range(1, len(split_list)):
                 split_list[i][0].replace(' ', '')
                 split_list[i][1].replace(' ', '')

                 if len(split_list[i]) > 2:
                     if split_list[i][-1] == 'M.D.':

                         split_list[i] = split_list[i][:-1]

                     if split_list[i][-1] == '':
                         split_list[i] = split_list[i][:-1]
                         split_list[i][-1] = split_list[i][-1].replace(',', '')
                 split_list[i][-1].replace(',', '')
             return split_list


         def join_list(some_list):
             joined = []
             for i in some_list:
                 joined.append(' '.join(i))
             return joined



         def match_name(name, list_names, min_score = 0):
```

```
        # -1 score incase we don't get any matches
        max_score = -1

        # Returning empty name for no match as well
        max_name = ""

        # Iternating over all names in the other
        for name2 in list_names:

            score3 = fuzz.ratio(''.join(name), ''.join(name2))

            # make sure they are from the same state
            if name2[-1].replace(',','') == name[-1].replace(',',''):

                # get similiarity scores
                score1 = fuzz.ratio(''.join(name), ''.join(name2))
                score2 = fuzz.partial_ratio(''.join(name), ''.join(name2))

                # and take the average of them
                score_av = (score1 + score2)/ 2

                if score3 > score_av:
                    score = score3
                if score3 <= score_av:
                    score = score_av

                # Checking if we are above our threshold and have a better score
                if (score > min_score) & (score > max_score):
                    max_name = name2
                    max_score = score
        return (' '.join(max_name), max_score)
```

In [23]:
```
# cleaning names
for i in range(2006,2017):
    murder_stats[i]['MSA'] = murder_stats[i]['MSA'].str.replace(' M.S.A.','')
    murder_stats[i]['MSA'] = murder_stats[i]['MSA'].str.replace('\d+','')
    murder_stats[i]['MSA'] = murder_stats[i]['MSA'].str.replace('\ue83a',' ')
    murder_stats[i]['MSA'] = murder_stats[i]['MSA'].str.replace('\nM.S.A.',' ')
    murder_stats[i]['MSA'] = murder_stats[i]['MSA'].str.replace('âĂŤ.',' ')
    murder_stats[i]['MSA'] = murder_stats[i]['MSA'].str.replace('urfrees',' ')
    murder_stats[i]['MSA'] = murder_stats[i]['MSA'].str.replace('M.S.A','')
    murder_stats[i]['MSA'] = murder_stats[i]['MSA'].str.replace('M.D.','')


    murder_stats[i].rename(columns={'Murder':'Murder ' + str(i)}, inplace = True)
```

```
        msa_year = murder_stats[i]['MSA'].tolist()
        clean_names = clean_split_names(msa_year)
        join_names = join_list(clean_names)
        murder_stats[i]['MSA'] = join_names
```

Below we match each FBI dataframe from a given year with the Census dataframe from the same year by first merging the dataframe, and finding the FBI MSA names that did not match and the Census MSA names that were not matched to. We use these names to find further matches, replacing the FBI names with the Census names. Last after we have replaced names, we merge the dataframe together again, and drop all the columns that do not match (some MSA's only appear in one dataset). We print the dimensions of the merged dfs before matching and after matching to show how well our matching works.

```
In [24]: # matching the names together and merging the dataframes
         for i in range(2006, 2017):

             # merge without any matching
             data = dict_df_year[i].merge(murder_stats[i],
                                          left_on='msa_name',
                                          right_on='MSA',
                                          how = 'outer',
                                         #since they are the same name, we need a suffix
                                       )
             # look at the shape (we want to see if this will decrease with matching)
             print(data.shape)

             # find the census names that haven't been matched
             census = data[data['MSA'].isnull()]['msa_name'].tolist()
             census_split = clean_split_names(census)

             # find the fbi names that haven't been matched
             fbi = data[data['msa_name'].isnull()]['MSA'].tolist()
             fbi_split = clean_split_names(fbi)

             dict_list = []
             names_replace = []

             # for every unmatched fbi names
             for name in fbi_split:

                     # return the best matched string in the census unmatched list if the match
                     match = match_name(name, census_split, 66.7)

                     # put into a dict
                     dict_ = {}
                     dict_.update({"FBI" : ' '.join(name)})
                     dict_.update({'Census' : match[0]})
                     dict_.update({"Score" : match[1]})
```

```
                dict_list.append(dict_)

                names_replace.append(match[0])

        # put into a df
        merge_table = pd.DataFrame(dict_list)

        # isolate the matches since unmatched will have a score of -1 by default
        replace_table = merge_table[merge_table['Score'] > 5][['FBI', 'Census']]

        # put matches in a dict with key: the str of fbi value: its census name match
        dict_replace = dict(zip(replace_table.FBI, replace_table.Census))

        # replace its name with the Census name
        murder_stats[i]['MSA'].update(murder_stats[i]['MSA'].map(dict_replace))

        # merge again after matching
        data2 = dict_df_year[i].merge(murder_stats[i],
                                      left_on = 'msa_name',
                                      right_on = 'MSA',
                                      how = 'inner',
                                     )
        data2 = data2[pd.notnull(data2['pop_' + '%02d' % (i - 2000)])]

        # this number should be now lower
        print(data2.shape, 'Should be less')


        # update the dictionary of dataframes
        dict_df_year[i] = data2
```

```
(445, 40)
(324, 40) Should be less
(456, 40)
(327, 40) Should be less
(455, 40)
(323, 40) Should be less
(471, 40)
(344, 40) Should be less
(461, 40)
(342, 40) Should be less
(472, 40)
(339, 40) Should be less
(508, 40)
(318, 40) Should be less
(510, 40)
(335, 40) Should be less
(502, 40)
```

```
(335, 40) Should be less
(497, 40)
(334, 40) Should be less
(507, 40)
(337, 40) Should be less
```

An example of the merged dataframe:
We drop the additional name column.

```
In [25]: for i in range(2006, 2017):
             dict_df_year[i] = dict_df_year[i].drop('MSA', axis = 1)
```

We now make the id's a column and reindex:

```
In [26]: # added ID's and saved the file
         for i in range(2006, 2017):
             unique_id = pd.DataFrame(np.c_[msa_df.index, msa_df['msa_name']], columns = ['ID','
             dict_df_year[i] = dict_df_year[i].merge(unique_id, left_on = 'msa_name', right_on =
```

2.1 BEA Data For Feature GDP per Capital

We add one more feature, gdp per capital for each year. This data was taken from the BEA.

```
In [27]: df_gdp = pd.read_csv('gdp_per_capita.csv')

         df_gdp.columns = ['IDs', 'MSA', 'gdp_06', 'gdp_07', 'gdp_08', 'gdp_09', 'gdp_10', 'gdp_
         df_gdp = df_gdp.drop(0)
         df_gdp.head()

Out[27]:      IDs                                                  MSA  gdp_06  gdp_07  \
         1  10180        Abilene, TX (Metropolitan Statistical Area)   33978   34883
         2  10420          Akron, OH (Metropolitan Statistical Area)   42081   42272
         3  10500         Albany, GA (Metropolitan Statistical Area)   32657   31885
         4  10540         Albany, OR (Metropolitan Statistical Area)   31331   29552
         5  10580  Albany-Schenectady-Troy, NY (Metropolitan Stat...   49549   48662

            gdp_08  gdp_09  gdp_10  gdp_11  gdp_12  gdp_13  gdp_14  gdp_15  gdp_16
         1   35663   33920   34004   33964   35406   37550   39776   39631   38385
         2   42633   40667   41138   40777   40687   41654   43750   46022   48195
         3   31376   31848   31036   30332   30578   30902   30005   29235   29073
         4   28153   27756   27049   27368   28171   27930   27520   28111   29328
         5   48504   49279   49716   49028   49548   49823   50149   51328   51755

In [28]: # add feature to each dictionary
         for i in range(2006, 2017):
```

```
    dict_df_year[i] = dict_df_year[i].merge(df_gdp[['IDs', 'gdp_' + '%02d' % (i - 2000)
                                left_on = 'ID',
                                right_on = 'IDs',
                                how = 'inner',
                             )
    dict_df_year[i] = dict_df_year[i].drop('IDs', axis = 1)
```

```
In [29]: # add to dict msa_df for plotting later
         dict_gdp_year = {}

         for i in range(2006, 2017):
             dict_gdp_year['gdp_' + '%02d' % (i - 2000)] = dict(zip(df_gdp['IDs'], df_gdp['gdp_'

         for key in dict_gdp_year:
             msa_df[key] = pd.Series(dict_gdp_year[key])
```

3 EDA

We make two columns for EDA. The first is murder_category which categorizes each year's murder counts by quartile. Up to the 25th percentile of 2016 numbers, murders are categorized with a 0 for low murder, from 25th to 75th they are categorized with a 1 for medium murder, and from 75th quartile and over, murders are categorized with a 2 for high.

We make another column called 'murder_rate', which takes the murder counts of each year and divides it by the population. Then we multiply it by 10,000 to make it murder per 10,000 people

```
In [30]: quantile = dict_df_year[2016]['Murder 2016'].quantile([0.25,0.5,0.75])
         print(quantile)

         how_murder = lambda x:((0, 1)[x > quantile[.25]], 2)[x > quantile[.75]]

         for i in range(2006, 2017):
             dict_df_year[i]['murder_category'] = dict_df_year[i]['Murder ' + str(i)].apply(how_
             dict_df_year[i]['pop_' + '%02d' % (i - 2000)] = dict_df_year[i]['pop_' + '%02d' % (
             dict_df_year[i]['murder_rate'] = dict_df_year[i]['Murder ' + str(i)] / dict_df_year
             dict_df_year[i]['murder_rate'] = dict_df_year[i]['murder_rate'] * 100000
```

```
0.25     4.0
0.50     9.0
0.75    26.0
Name: Murder 2016, dtype: float64
```

3.1 Feature Trend Lines

In order to determine how the features have changed over time, we select four MSA's. In particular, Chicago-Naperville-Joliet, IL-IN-WI, Rochester, Duluth, MN-WI, Philadelphia-Camden-

Wilmington, PA-NJ-DE-MD, Panama City-Lynn Haven, FL from 2016 counts. One of the MSA"s is in the low murder category, another is the medium murder category, and the other two are in the high murder category.

In [31]:
```
### pick some cities of interest based on murder rates/row choice in 2016

def find_nearest(array, value):
    idx = (np.abs(array - value)).argmin()
    return idx

murders_16 = dict_df_year[2016]['Murder 2016']

maxidx = np.argmax(murders_16)
minidx = np.argmin(murders_16)

mediumidx = find_nearest(murders_16, (max(murders_16) + min(murders_16)) / 2)
sub_16 = dict_df_year[2016].iloc[[maxidx, 86, mediumidx, 211], :]
sub_ids = sub_16['ID'].tolist()

sub_16
```

Out[31]:
```
      pop_16  Percent_male_16  Percent_female_16  AGE - Under 5 years_16  \
54   9512968         0.489620           0.510380                     6.1
86    279227         0.505678           0.494322                     5.1
214  6070500         0.483860           0.516140                     5.9
211   200893         0.504821           0.495179                     5.9

     AGE - 5 to 9 years_16  AGE - 10 to 14 years_16  AGE - 15 to 19 years_16  \
54                     6.4                      6.7                      6.7
86                     5.1                      6.2                      6.9
214                    6.1                      6.2                      6.5
211                    6.7                      4.8                      6.2

     AGE - 20 to 24 years_16  AGE - 25 to 29 years_16  \
54                       6.8                      7.2
86                       8.1                      5.8
214                      6.6                      7.4
211                      6.3                      7.1

     AGE - 30 to 34 years_16     ...       Asian alone_Percent_16  \
54                       7.1     ...                     0.064895
86                       5.8     ...                     0.010687
214                      6.8     ...                     0.058514
211                      6.5     ...                     0.027920

     Native Hawaiian and Other Pacific Islander alone_Percent_16  \
54                                            0.000387
86                                            0.000161
```

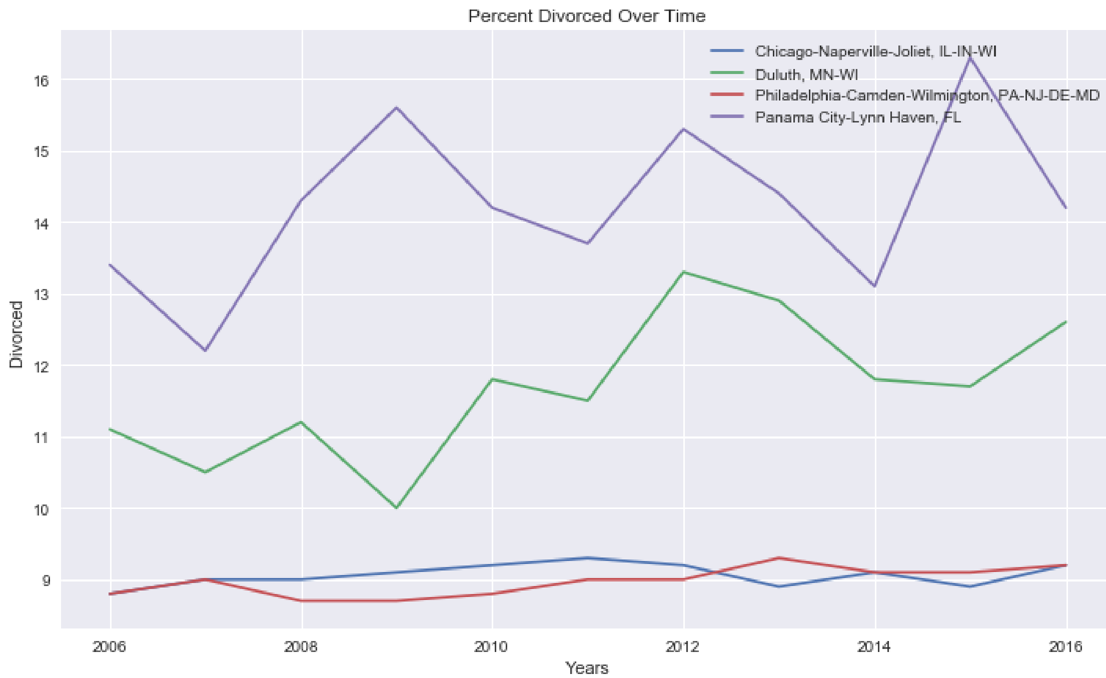
```
214                                             0.000357
211                                             0.000169

     Some other race alone_Percent_16  Two or more races:_Percent_16  \
54                           0.087865                       0.026341
86                           0.004136                       0.023132
214                          0.034570                       0.028379
211                          0.005306                       0.030763

                                         msa_name  Murder 2016     ID  gdp_16  \
54           Chicago-Naperville-Joliet, IL-IN-WI        958.0  16980   59810
86                                  Duluth, MN-WI          3.0  20260   39814
214  Philadelphia-Camden-Wilmington, PA-NJ-DE-MD        480.0  37980   62817
211                    Panama City-Lynn Haven, FL          9.0  37460   36374

     murder_category  murder_rate
54                 2    10.070464
86                 0     1.074395
214                2     7.907092
211                1     4.479997

[4 rows x 43 columns]
```

We define a function that will plot the feature name over 2006-2016 for specified MSAs

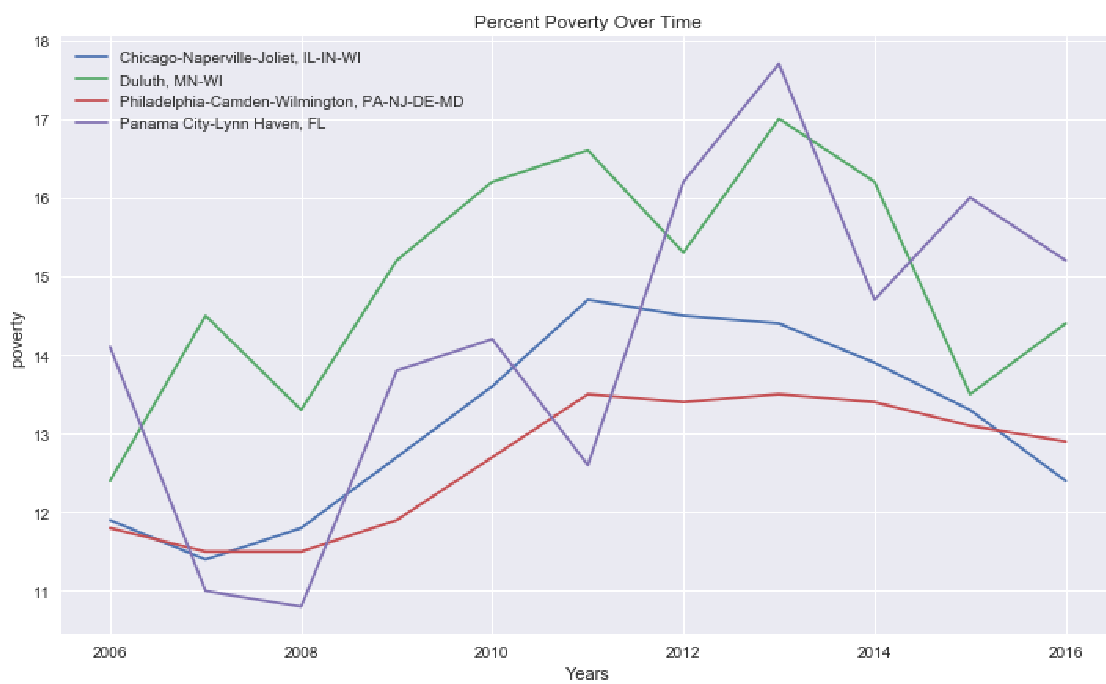
In [32]:
```
# use msa just for the feature trends
# function can take ids of MSA's and features and plot the trend of that feature in tim
def trend_plot(feature_name, sub_ids, title):
    pc_temp = []
    for i in range(2006, 2017):
        pc_temp.append(msa_df.loc[sub_ids].columns.get_loc(feature_name + '%02d' % (i -

    df_temp = msa_df.loc[sub_ids].iloc[:, pc_temp]
    df_temp.loc[len(df_temp)] = np.arange(2006, 2017, 1)
    df_temp = df_temp.T
    new_cols = msa_df.loc[sub_ids]['msa_name'].tolist()
    new_cols.append('year')
    df_temp.columns = new_cols
    plt.figure(figsize = (12, 7))

    for i in range(len(sub_ids)):
        plt.plot(df_temp['year'].values,df_temp.iloc[:,i].values,label = df_temp.column
    plt.legend(loc = 'best')
    plt.xlabel('Years')
    plt.ylabel(feature_name.replace("_", " "))
    plt.title(title)
```

We plot some of the features below:

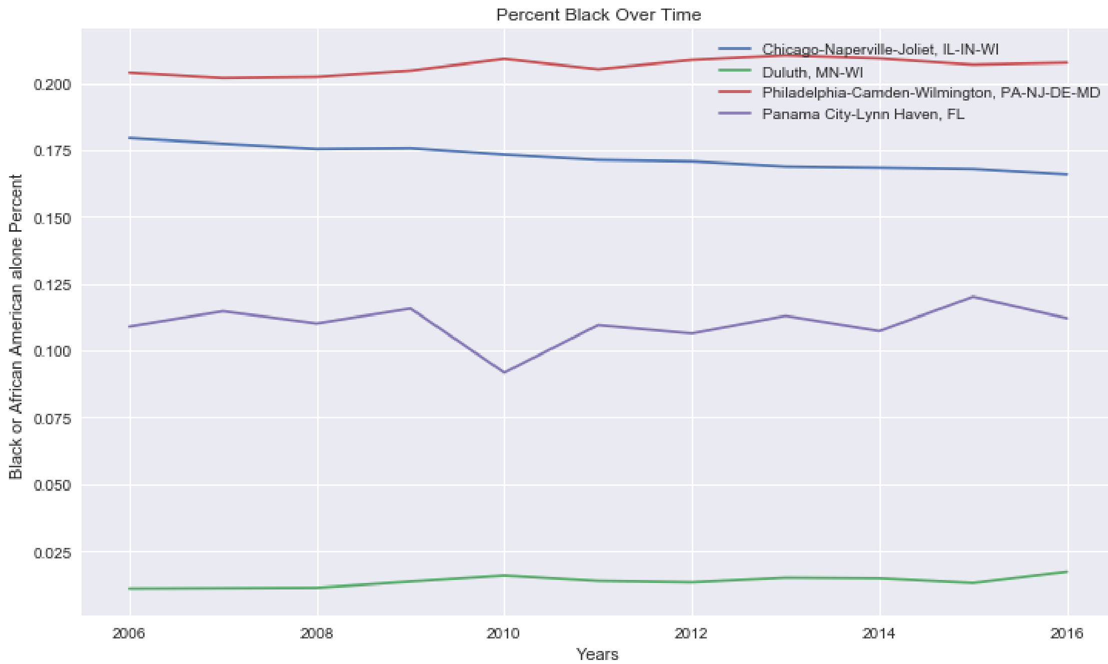
```
In [33]: trend_plot('Divorced_', sub_ids, 'Percent Divorced Over Time')
```



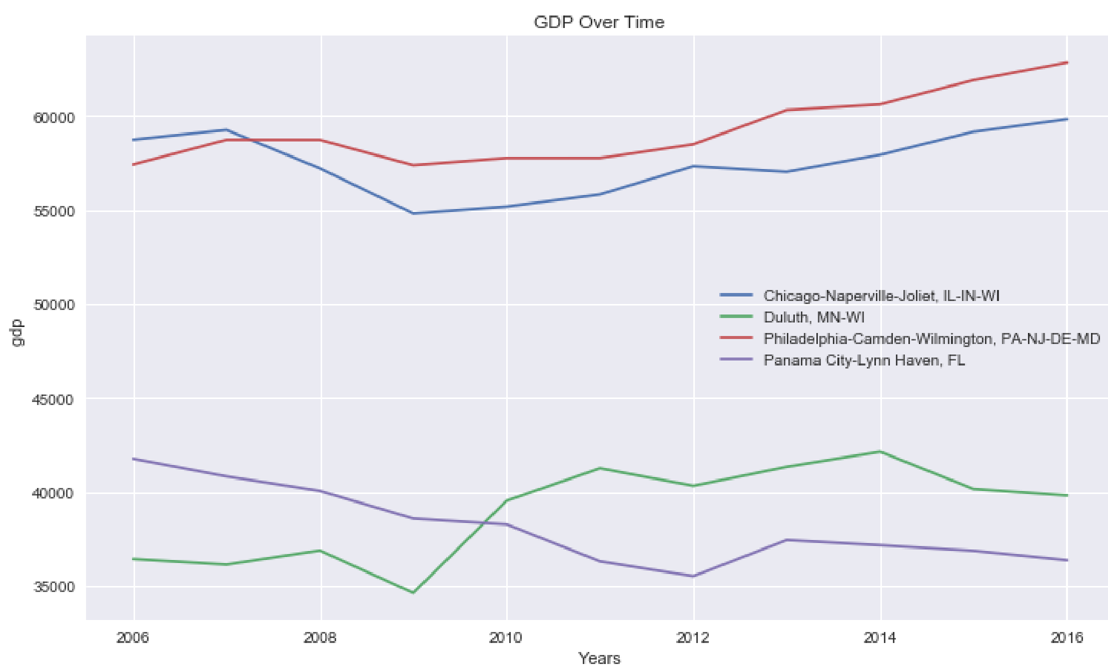

```
In [34]: trend_plot('poverty_', sub_ids, 'Percent Poverty Over Time')
```



In [35]: trend_plot('Black or African American alone_Percent_', sub_ids, 'Percent Black Over Tim



In [36]: trend_plot('gdp_', sub_ids, 'GDP Over Time')



3.2 Murder Over Time

In [37]:
```
sub_years = {}
for i in range(2006,2017):
    sub_years[i] = dict_df_year[i].loc[dict_df_year[i]['ID'].isin(sub_ids)]
```

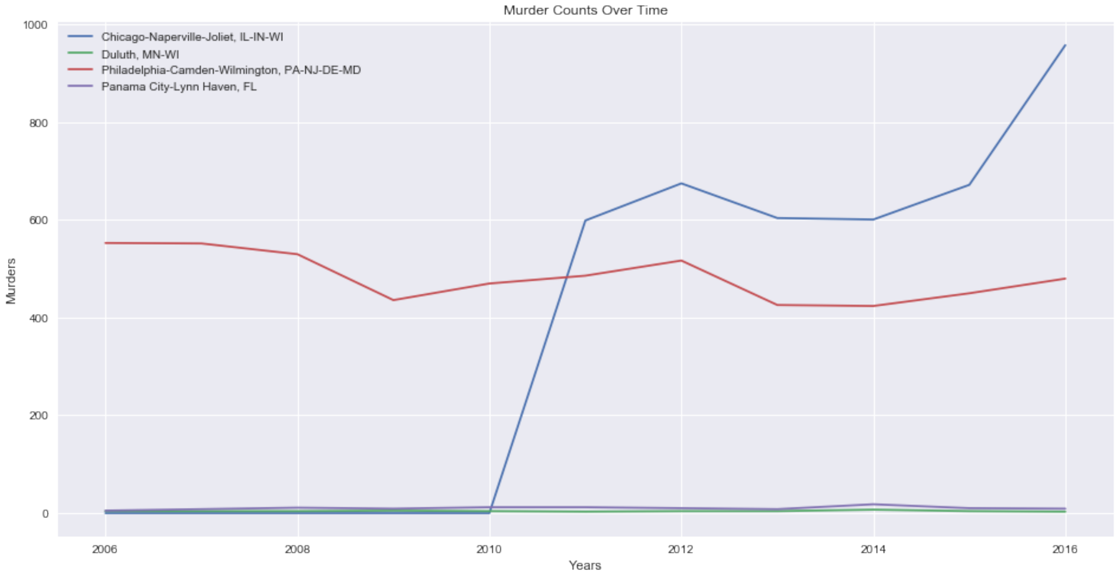
In [38]:
```
sub_years[2008].head()
```

Out[38]:
```
       pop_08  Percent_male_08  Percent_female_08  AGE - Under 5 years_08  \
76     275336         0.494599           0.505401                     5.5
208    163946         0.490924           0.509076                     6.6
210   5838471         0.483937           0.516063                     6.5

     AGE - 5 to 9 years_08  AGE - 10 to 14 years_08  AGE - 15 to 19 years_08  \
76                     5.7                      5.3                      7.7
208                    6.9                      6.1                      6.2
210                    6.4                      6.6                      7.5

     AGE - 20 to 24 years_08  AGE - 25 to 29 years_08  \
76                       8.4                      6.6
208                      5.4                      6.8
210                      6.7                      5.9

     AGE - 30 to 34 years_08     ...       Asian alone_Percent_08  \
76                       5.4     ...                     0.006505
208                      6.4     ...                     0.017579
210                      5.9     ...                     0.043522

     Native Hawaiian and Other Pacific Islander alone_Percent_08  \
76                                            0.000000
208                                           0.002049
210                                           0.000195

     Some other race alone_Percent_08  Two or more races:_Percent_08  \
76                           0.000701                       0.017161
208                          0.004264                       0.040751
210                          0.028367                       0.017605

                                         msa_name  Murder 2008     ID  gdp_08  \
76                                  Duluth, MN-WI          4.0  20260   36885
208                      Panama City-Lynn Haven, FL         11.0  37460   40052
210   Philadelphia-Camden-Wilmington, PA-NJ-DE-MD        530.0  37980   58708

     murder_category  murder_rate
76                 0     1.452770
208                1     6.709526
210                2     9.077719

[3 rows x 43 columns]
```

In [39]:
```
# looks at sub years and checks whether all ids are there and extracts murders
# if some id's are missing, murders for those are set to zero (e.g. Chicago from 2006 t
def find_yw_data(sub_years, sub_ids):
    main = []
    for i in range (2006,2017):
        temp = []
        for j in sub_ids:
            if sum((sub_years[i]['ID'])== j) == 1:
                temp.append(sub_years[i][sub_years[i]['ID'] == j]['Murder '+ str(i)].va
            else:
                temp.append(0)
        main.append(temp)
    return(main)
```

In [40]:
```
# use msa just for the feature trends
# plots murder trends given MSA indices
def murder_trend_plot(sub_ids):
    murder_years = np.array(find_yw_data(sub_years,sub_ids))
    new_cols = msa_df.loc[sub_ids]['msa_name'].tolist()
    x = np.arange(2006,2017,1)
    plt.figure(figsize=(16, 8))
    for i in range(len(sub_ids)):
        plt.plot(x,murder_years[:,i],label = new_cols[i])
    plt.legend(loc='best')
    plt.xlabel('Years')
    plt.ylabel('Murders')
    plt.title('Murder Counts Over Time')
```

In [41]:
```
murder_trend_plot(sub_ids)
```

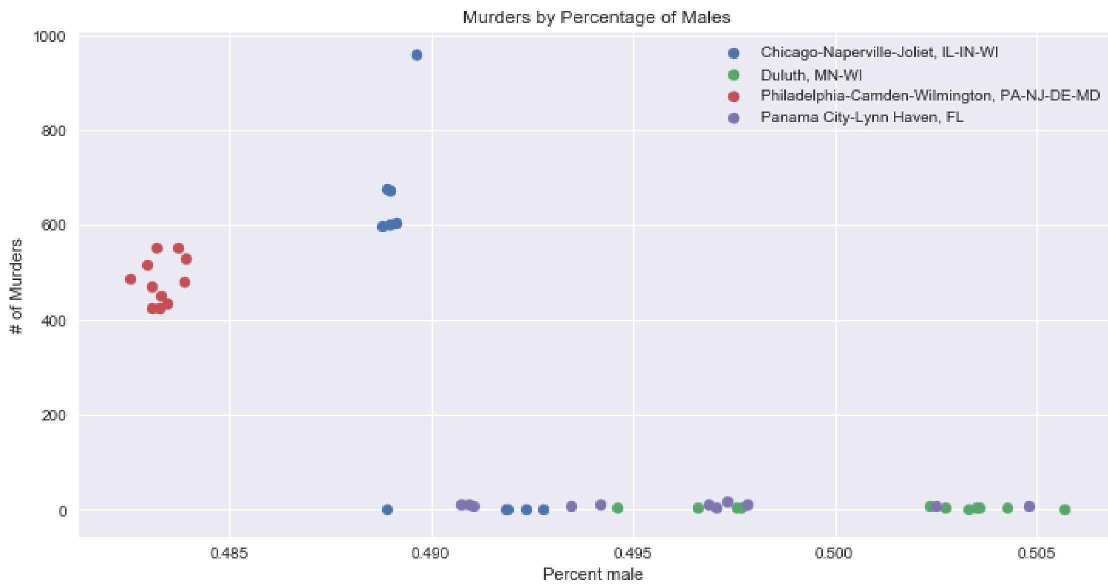


3.3 Murder by Feature

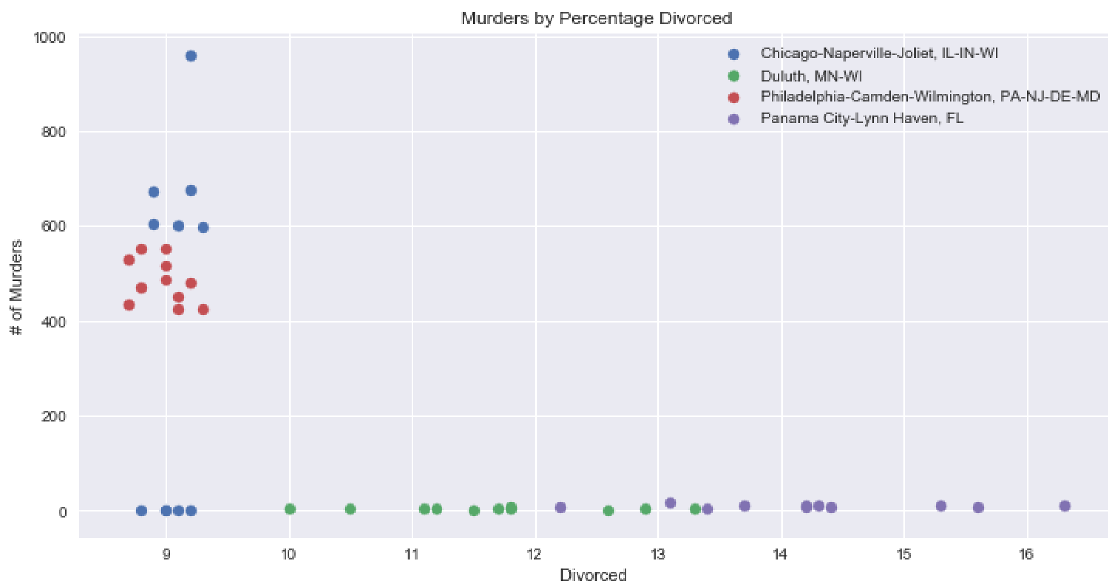
```
In [42]: # use msa just for the feature trends
         # scatter plot of feature against the murder with data from all years

         def feature_murder_plot(feature_name, sub_ids, title):
             pc_temp =[]
             sub_years = {}
             for i in range(2006, 2017):
                 sub_years[i] = dict_df_year[i].loc[dict_df_year[i]['ID'].isin(sub_ids)]

             for i in range(2006,2017):
                 pc_temp.append(msa_df.loc[sub_ids].columns.get_loc(feature_name + '%02d' %(i -
             murder_years = np.array(find_yw_data(sub_years, sub_ids))
             # index all rows with interesting sub ids and feature of interest columns
             df_temp = msa_df.loc[sub_ids].iloc[:,pc_temp]
             # add row for years
             df_temp.loc[len(df_temp)] = np.arange(2006, 2017, 1)
             df_temp = df_temp.T
             new_cols = msa_df.loc[sub_ids]['msa_name'].tolist()
             new_cols.append('year')
             df_temp.columns = new_cols
             plt.figure(figsize=(12, 6))
             for i in range(len(sub_ids)):
                 plt.scatter(df_temp.iloc[:,i].values,murder_years[:,i],label = new_cols[i])
             plt.legend(loc='best')
             plt.ylabel('# of Murders')
             plt.xlabel(feature_name.replace("_", " "))
             plt.title(title)
```

We plot some of the features below:

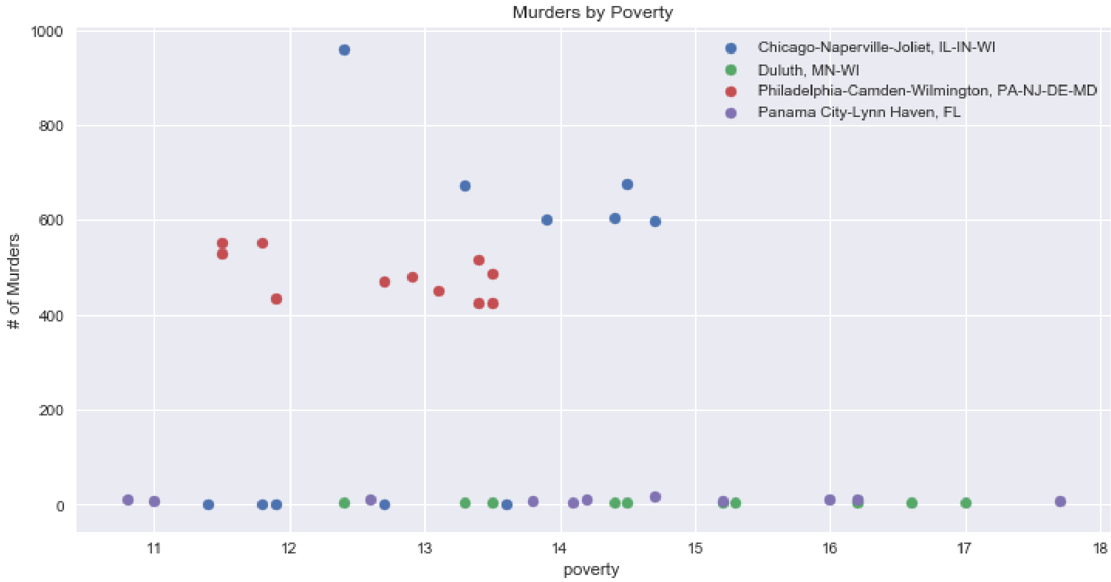
```
In [43]: feature_murder_plot('Percent_male_', sub_ids, 'Murders by Percentage of Males')
```



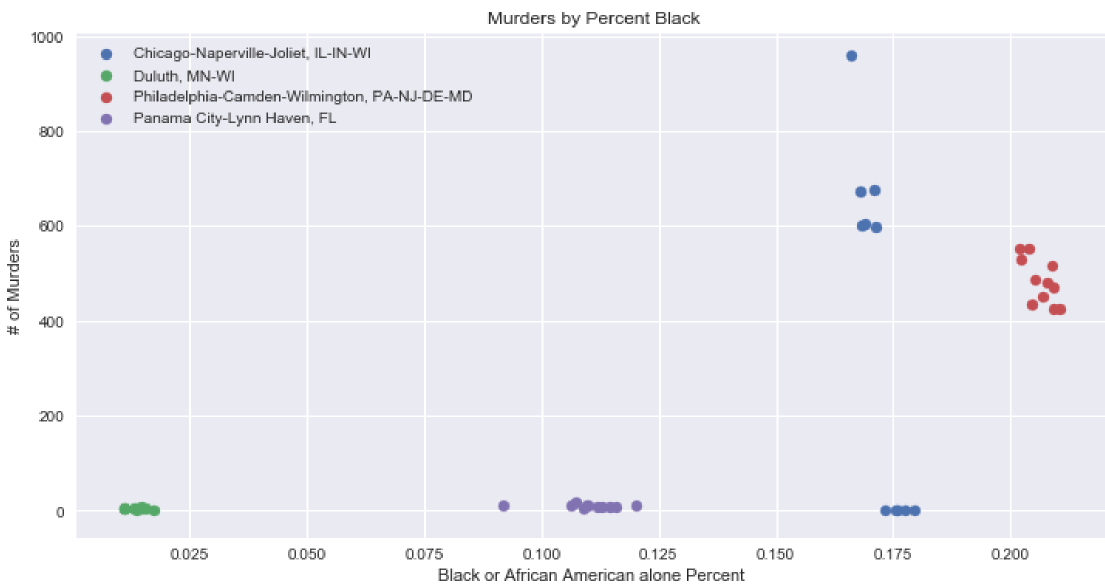

```
In [44]: feature_murder_plot('Divorced_', sub_ids, 'Murders by Percentage Divorced')
```




```
In [45]: feature_murder_plot('poverty_', sub_ids, 'Murders by Poverty')
```




```
In [46]: feature_murder_plot('Black or African American alone_Percent_', sub_ids, 'Murders by Pe
```



3.4 Murder on Map of US

We use Geopy to find the longitude and latitiude of each MSA and plot them on a map'

```
In [47]: ## find lat and long for each msa
         geolocator = Nominatim()
         # lat_long = []
         # for row in unique_id['msa_name']:
         #     if geolocator.geocode(row) == None:
         #         lat_long.append(np.nan)
         #     if geolocator.geocode(row) != None:
         #         lat_long.append(geolocator.geocode(row)[1])

         # # save as file
         # with open('outfile', 'wb') as fp:
         #     pickle.dump(lat_long, fp)

         # read in file
         with open ('outfile', 'rb') as fp:
             llng = pickle.load(fp)

         # split by latitude and longitude
         lat = []
         long = []
         for i in llng:
             if type(i) is float:
                 lat.append(np.nan)
                 long.append(np.nan)
             if type(i) is tuple:
                 lat.append(i[0])
                 long.append(i[1])

         lat_long_df = pd.DataFrame([unique_id['ID'].tolist(), lat, long]).T

         # some of the lat_longs were wrong
         lat_long_df.columns = ['ID', 'latitude', 'longitude']

In [48]: # add to each df
         position_murder_df = {}
         for i in range(2006, 2017):
             position_murder_df[i] = dict_df_year[i].merge(lat_long_df, left_on = 'ID', right_on

In [49]: # some lat and long were wrong so we drop them
         position_murder_df[2006] = position_murder_df[2006][position_murder_df[2006]['msa_name'
         position_murder_df[2016] = position_murder_df[2016][position_murder_df[2016]['msa_name'

In [50]: plotly.tools.set_credentials_file(username ='jeanettejin', api_key ='65684eh97DVINyUzjc

         data = [dict(
             lat = position_murder_df[2006]['latitude'],
             lon = position_murder_df[2006]['longitude'],
             text =  position_murder_df[2006]['Murder 2006'].astype(str) + ' count',
```

```
    marker = dict(
        size = 10,
        color = position_murder_df[2006]['Murder 2006'],
        colorsrc = "jeanettejin:2:236ccc",
        opacity = 1.0,
        colorscale =  [[0, 'rgb(49,54,149)'], [1./10000, 'rgb(69,117,180)'], [1./1000,
        colorbar = dict(
            thickness = 10,
            titleside = "right",
            outlinecolor = "rgba(68, 68, 68, 0)",
            ticklen = 3,
            showticksuffix = 'first',
            ticksuffix = " count",
        ),
    ),
    type = 'scattergeo',
) ]

layout = dict(
    geo = dict(
        scope = 'north america',
        showland = True,
        landcolor = "rgb(212, 212, 212)",
        subunitcolor = "rgb(255, 255, 255)",
        countrycolor = "rgb(255, 255, 255)",
        showlakes = True,
        lakecolor = "rgb(255, 255, 255)",
        showsubunits = True,
        showcountries = True,
        resolution = 50,
        projection = dict(
            type = 'conic conformal',
            rotation = dict(
                lon = -100
            )
        ),
        lonaxis = dict(
            showgrid = True,
            gridwidth = 0.5,
            range= [ -140.0, -55.0 ],
            dtick = 5
        ),
        lataxis = dict (
            showgrid = True,
            gridwidth = 0.5,
            range= [ 20.0, 60.0 ],
            dtick = 5
```

```
            )
        ),
        title = 'Murder Counts in US 2006',
    )
    fig = {'data': data, 'layout': layout }
    py.iplot(fig, filename = 'Murder_2006')
```

Out[50]: <plotly.tools.PlotlyDisplay object>

In [51]:

```
plotly.tools.set_credentials_file(username ='jeanettejin', api_key ='65684eh97DVINyUzjc

data = [dict(
    lat = position_murder_df[2016]['latitude'],
    lon = position_murder_df[2016]['longitude'],
    text =  position_murder_df[2016]['Murder 2016'].astype(str) + ' count',

    marker = dict(
        size = position_murder_df[2016]['Murder 2016'] / 10,
        color = 'red',
        colorsrc = "jeanettejin:2:236ccc",
        opacity = 1.0,
    ),
    type = 'scattergeo',
) ]

layout = dict(
    geo = dict(
        scope = 'north america',
        showland = True,
        landcolor = "rgb(212, 212, 212)",
        subunitcolor = "rgb(255, 255, 255)",
        countrycolor = "rgb(255, 255, 255)",
        showlakes = True,
        lakecolor = "rgb(255, 255, 255)",
        showsubunits = True,
        showcountries = True,
        resolution = 50,
        projection = dict(
            type = 'conic conformal',
            rotation = dict(
                lon = -100
            )
        ),
        lonaxis = dict(
            showgrid = True,
            gridwidth = 0.5,
            range= [ -140.0, -55.0 ],
            dtick = 5
```

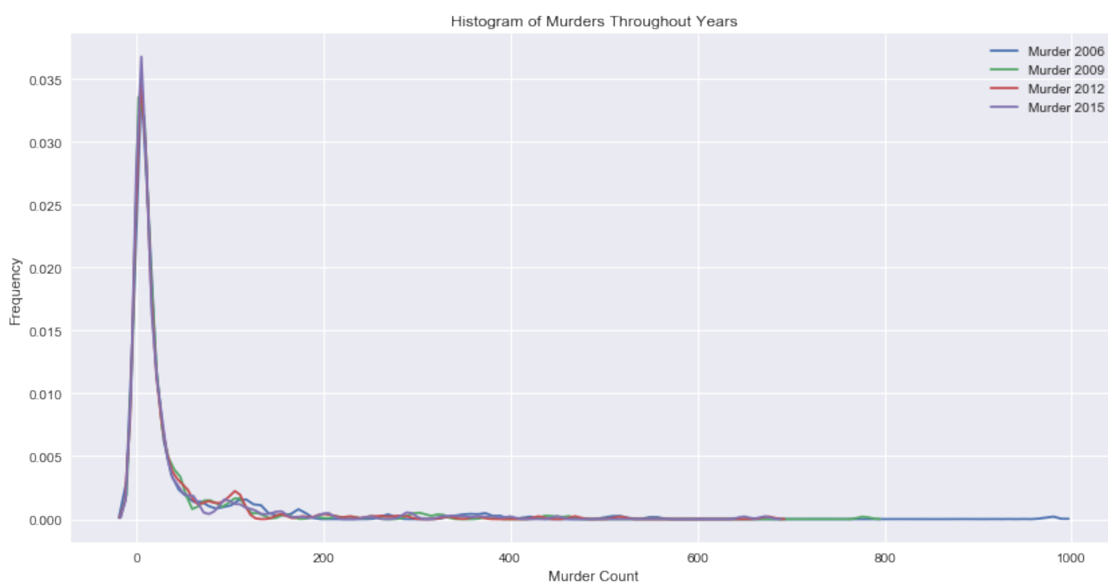
```
                ),
                lataxis = dict (
                    showgrid = True,
                    gridwidth = 0.5,
                    range= [ 20.0, 60.0 ],
                    dtick = 5
                )
            ),
            title = 'Murder Counts in US 2016',
        )
        fig = {'data': data, 'layout': layout }
        py.iplot(fig, filename = 'Murder_2016')
```

```
Out[51]: <plotly.tools.PlotlyDisplay object>
```

3.5 Histograms of Murders Across Years

We can see that most MSA have pretty low murder counts

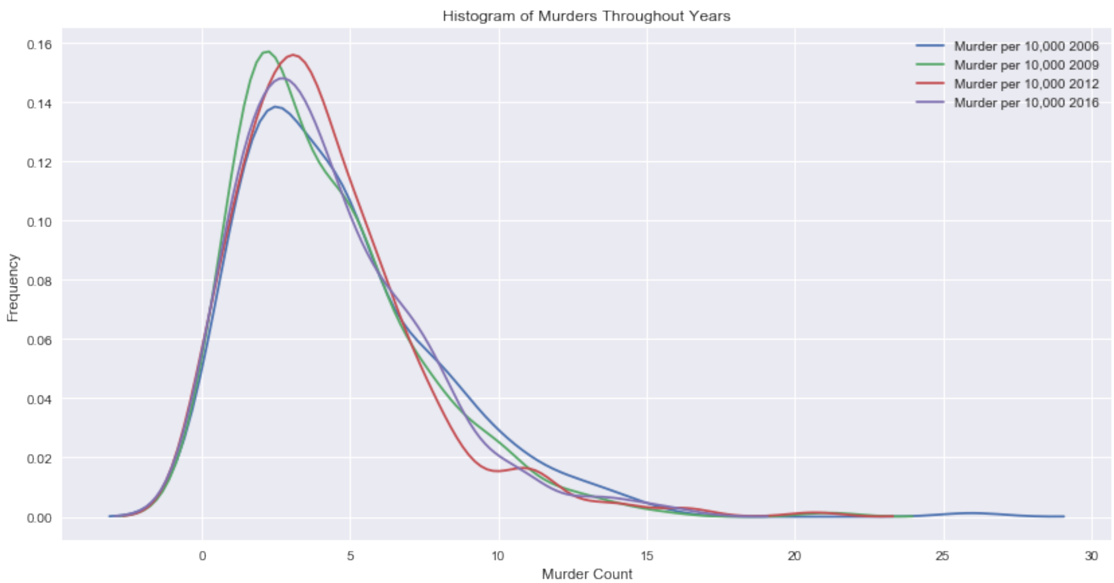
```
In [52]: fig, ax = plt.subplots(figsize=(14, 7))
        ax.set(xlabel = 'Murder Count', ylabel = 'Frequency')
        ax.set_title("Histogram of Murders Throughout Years")


        for i in range(2006, 2017, 3):
            sns.kdeplot(dict_df_year[i]['Murder ' + str(i)], ax = ax)
```




```
In [53]: fig, ax = plt.subplots(figsize=(14, 7))
        ax.set(xlabel = 'Murder Count', ylabel = 'Frequency')
```

```
ax.set_title("Histogram of Murders Throughout Years")


for i in range(2006, 2017, 3):
    sns.kdeplot(dict_df_year[i]['murder_rate'], ax = ax)


plt.legend(['Murder per 10,000 2006', 'Murder per 10,000 2009', 'Murder per 10,000 2012
```

Out[53]: <matplotlib.legend.Legend at 0x1242037b8>



3.6 Feature vs Murder or Murder / Population by Group Through TIme

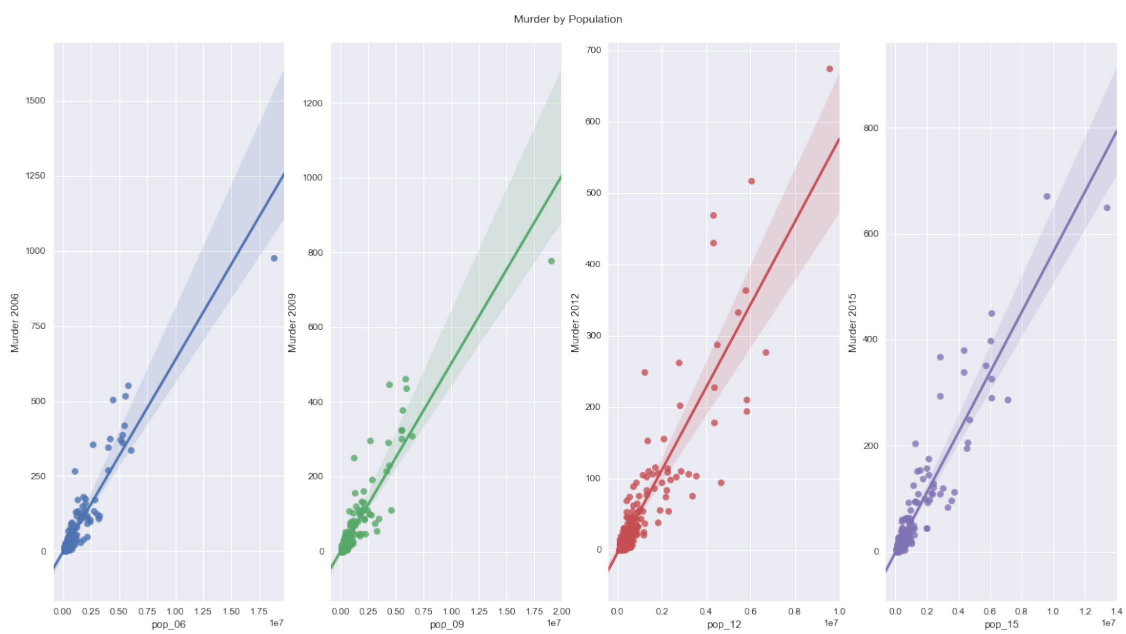
We define a function that plots murder's by feature in certain circumstances, plotted throughout various years. If option is 0 we plot murder by feature for various years. If option is 1, we plot murder by feature and differerentiate each point by weather it's murder_category is low, medium, or high across multiple years. If option is 2, we plot murder divided by population by feature across multiple years.

In [54]:
```
def feature_x_time(title, feature, option = 0):

    if option is 0:
        fig, ax = plt.subplots(1, 4, figsize=(20, 10))
        plt.subplots_adjust(top = .94)
        fig.suptitle(title)
        for i in range(2006, 2017, 3):
            ind = int((i - 2006) / 3)
```

```
                sns.regplot(feature + '%02d' % (i - 2000), 'Murder ' + str(i), dict_df_year
                sns.set(font_scale = .7)

        if option is 1:
            for i in range(2006, 2017, 3):
                ind = int((i - 2006) / 3)
                sns.lmplot(feature + '%02d' % (i - 2000), 'Murder ' + str(i), hue = "murder

        if option is 2:
            fig, ax = plt.subplots(1, 4, figsize=(20, 10))
            plt.subplots_adjust(top = .94)
            fig.suptitle(title)

            for i in range(2006, 2017, 3):
                ind = int((i - 2006) / 3)
                sns.regplot(feature + '%02d' % (i - 2000), 'murder_rate', dict_df_year[i],
                ax[ind].set(ylim=(0, 6))
```

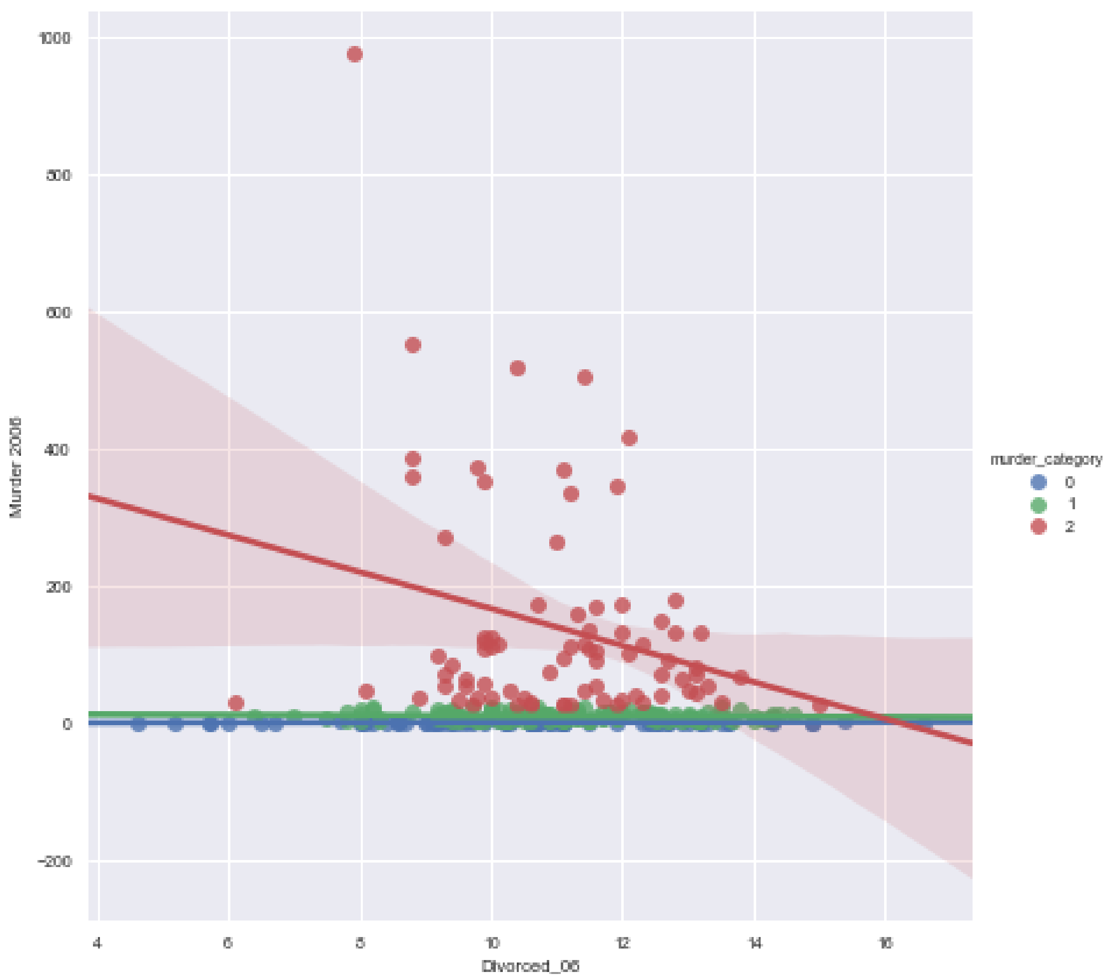
We can see that murder and population seem to have a strong linear relationship. For the remainder of the variables, we also include option 2, so we can see how each feature varies with murder/population

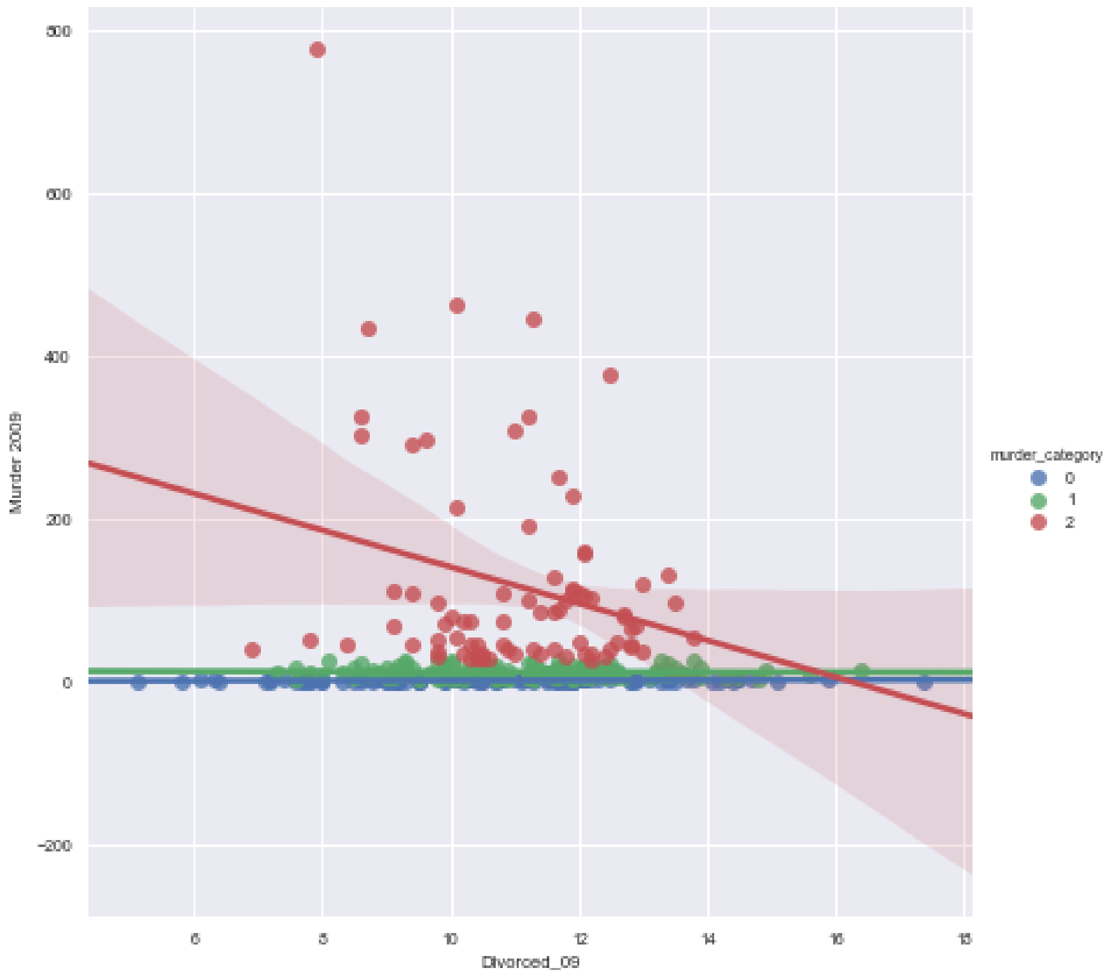
```
In [55]: feature_x_time("Murder by Population", 'pop_')
```



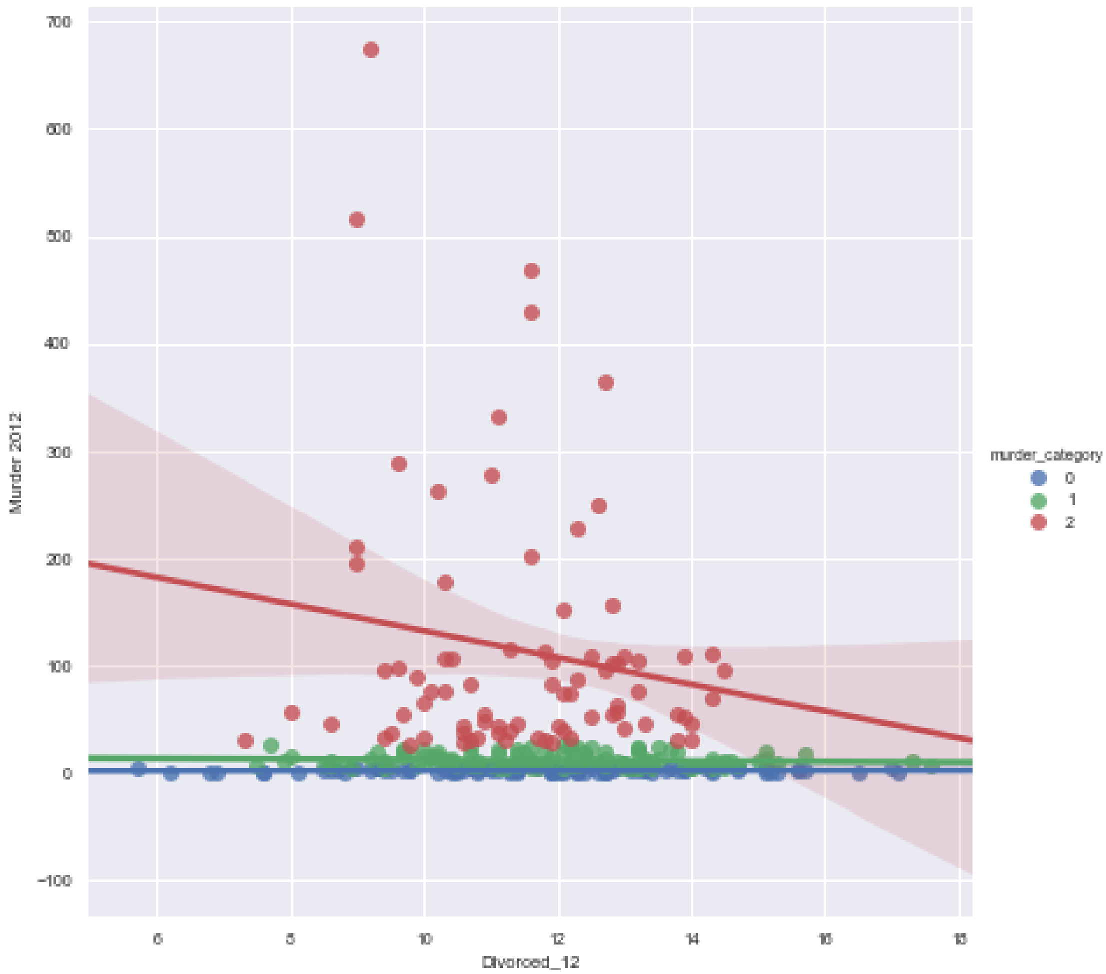

```
In [56]: feature_x_time("Percent Divorced and Murder Across Time", "Divorced_")
```


```
In [57]: feature_x_time("Percent Divorced and Murder Across Time", "Divorced_", option = 1)
```

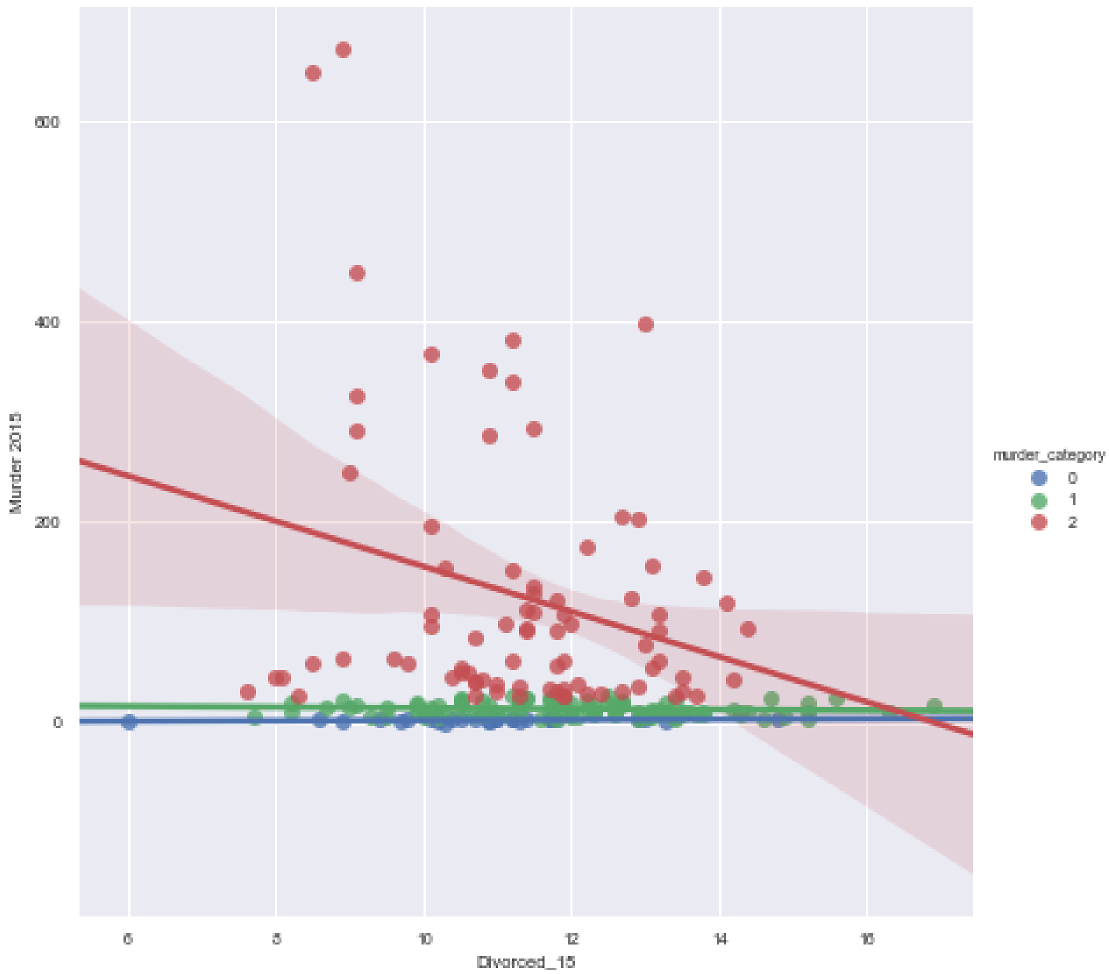

1000
800
600
400
200
0
−200
Murder 2006
4
6
8
10
12
14
16
Divorced_06
murder_category
0
1
2



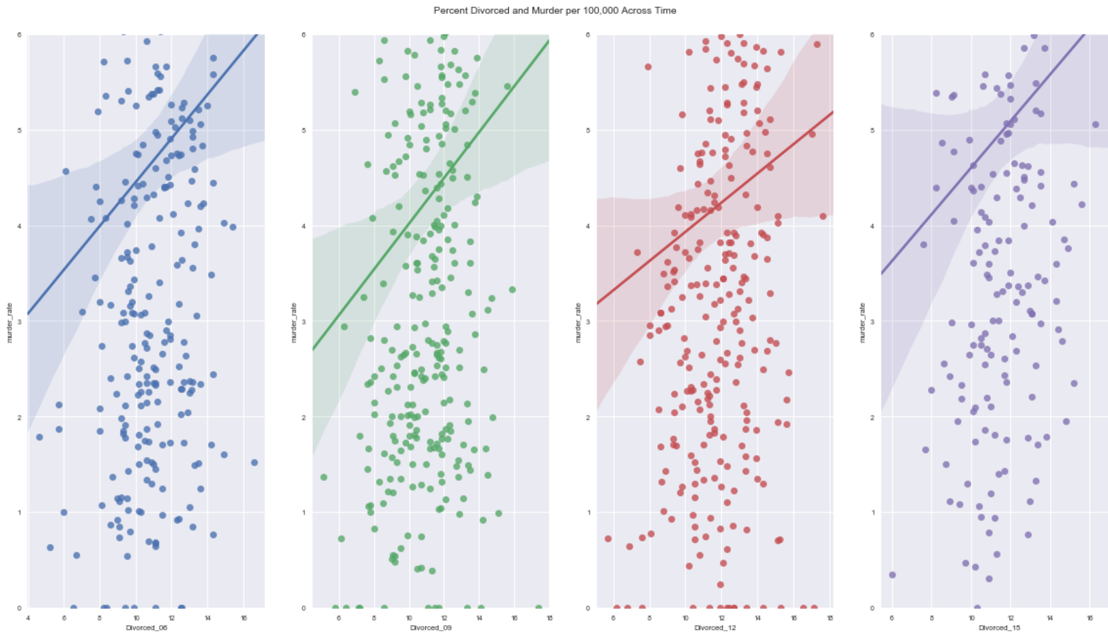
Murder 2009
Divorced_09
murder_category
0
1
2



700
600
500
400
300
200
100
0
−100
Murder 2012
Divorced_12
10
12
14
16
murder_category
0
1
2

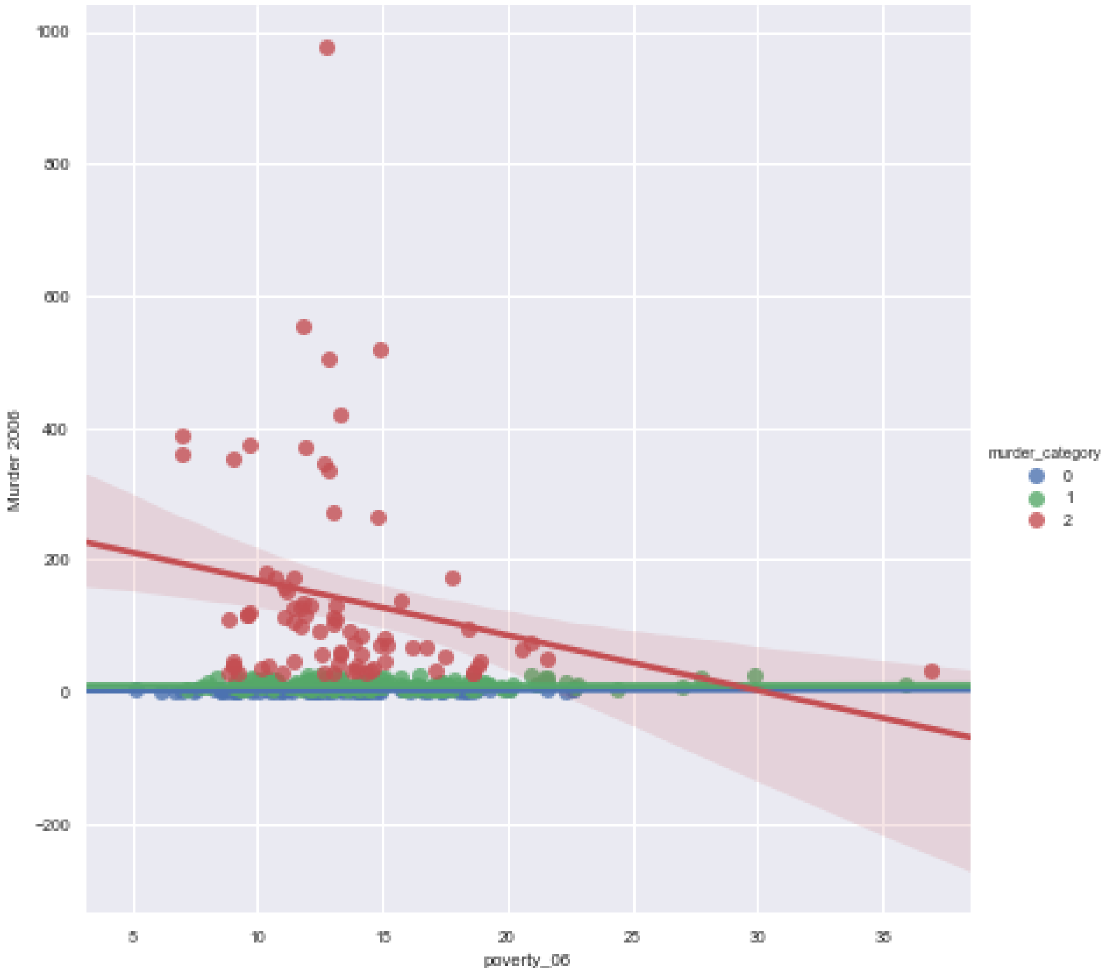



```
In [58]: feature_x_time("Percent Divorced and Murder per 100,000 Across Time", "Divorced_", opti
```

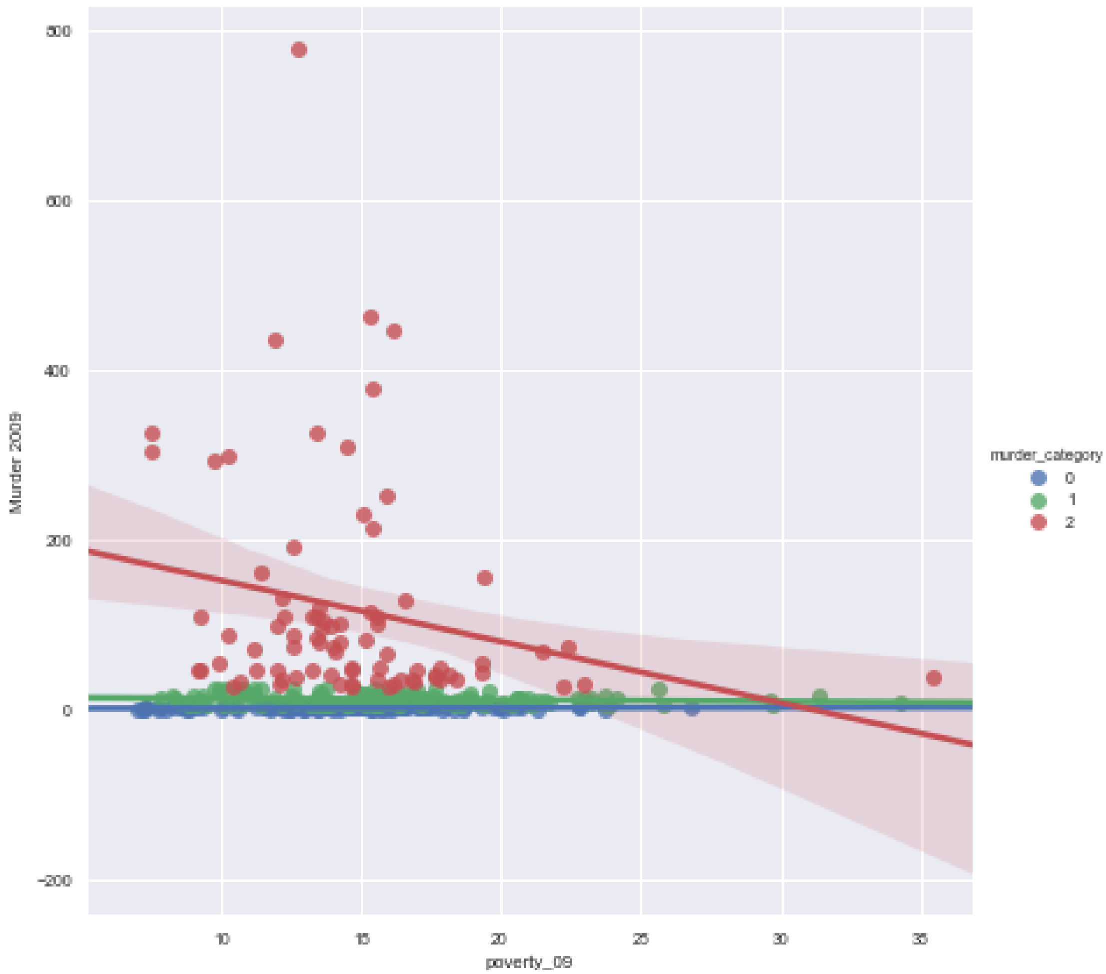



```
In [59]: feature_x_time('Poverty and Murder Across Time', 'poverty_')
```

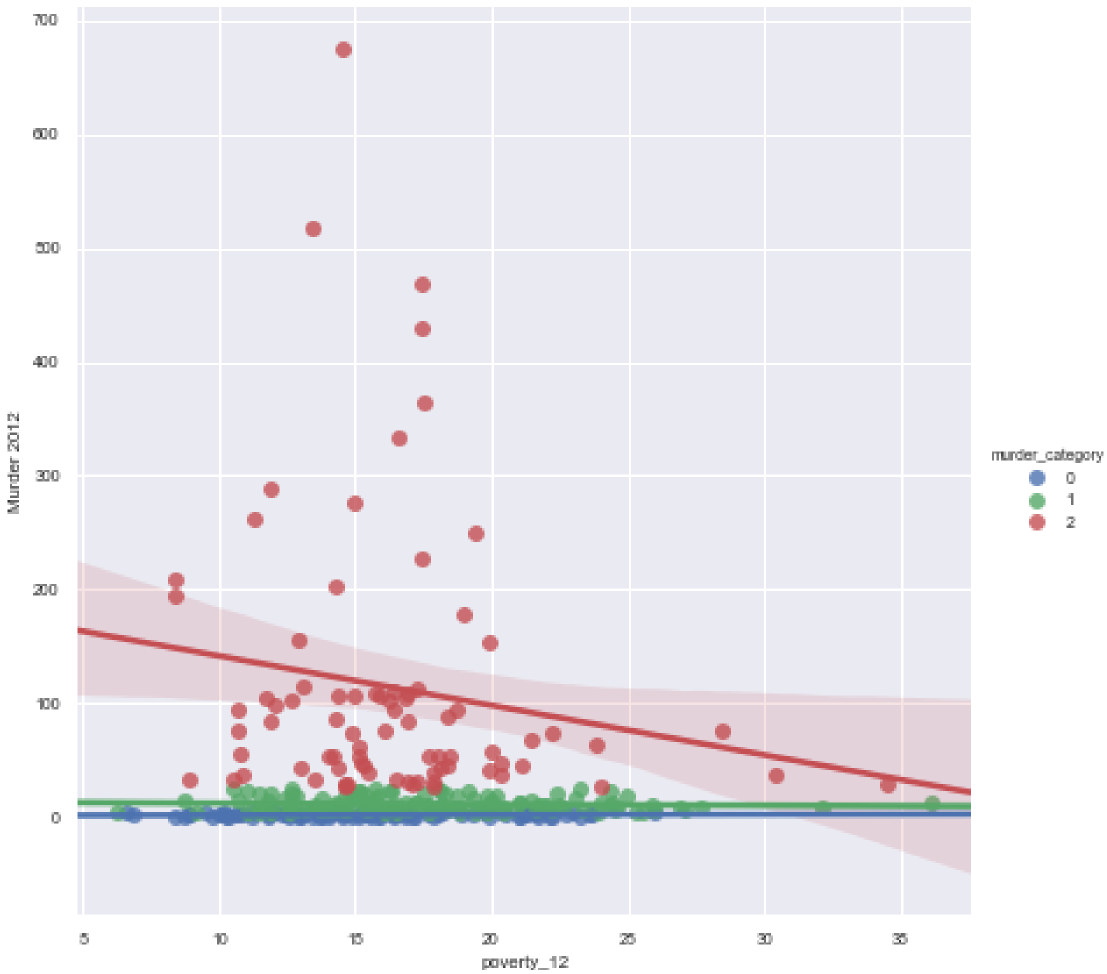

```
In [60]: feature_x_time('Poverty and Murder Across Time', 'poverty_', option = 1)
```

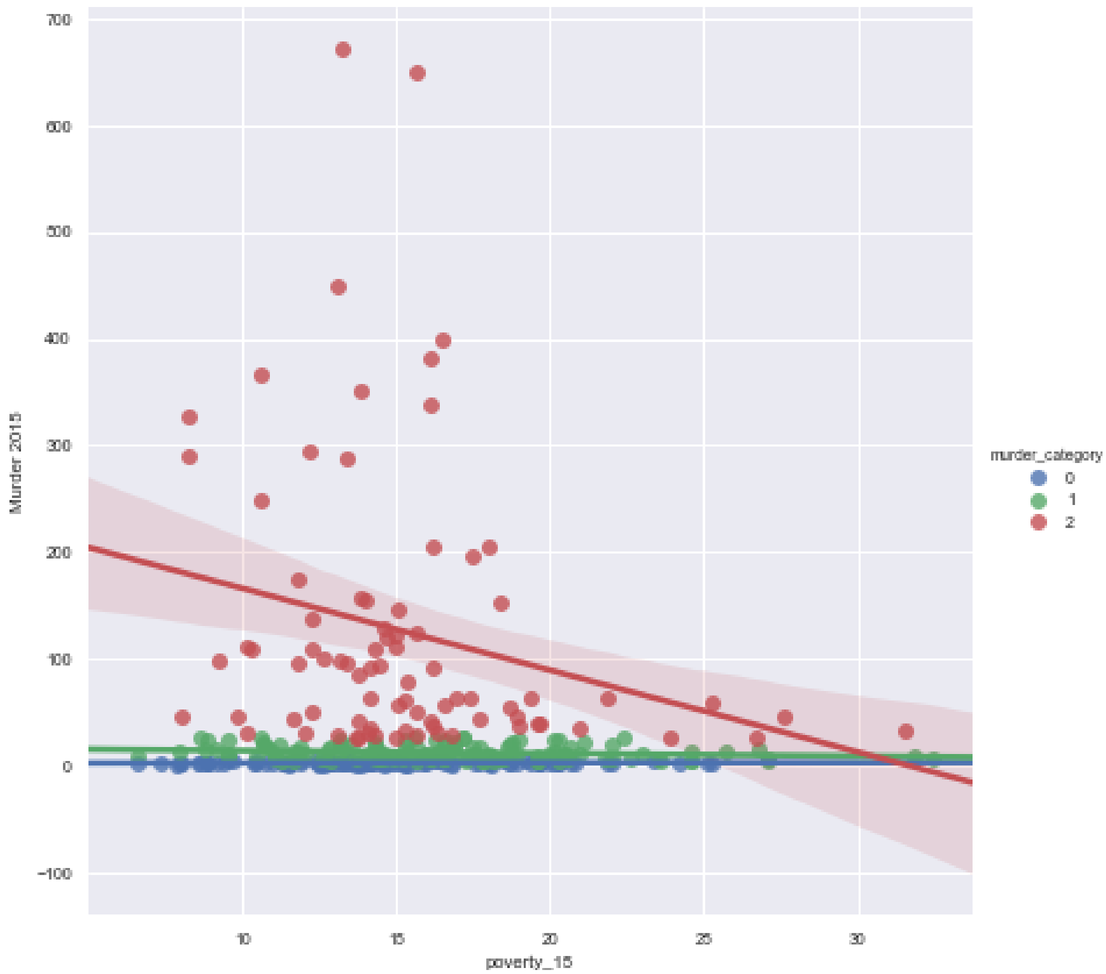


1000
800
600
400
200
0
−200
Murder 2006
5
10
15
20
25
30
35
poverty_06
murder_category
0
1
2

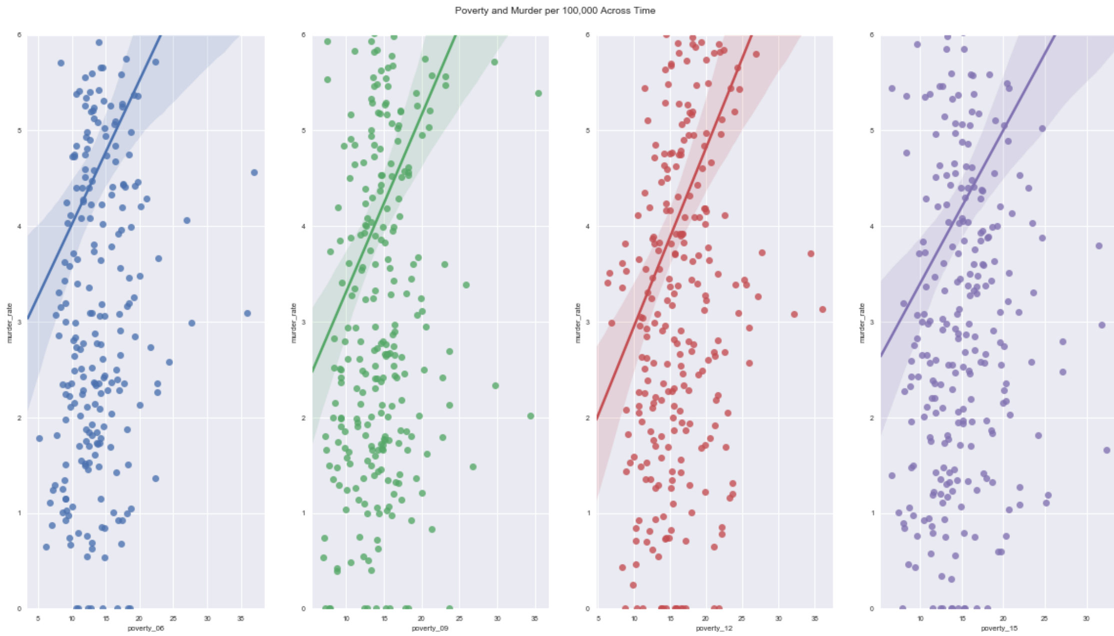


800
600
400
200
0
−200
Murder 2009
10
15
20
25
30
35
poverty_09
murder_category
0
1
2

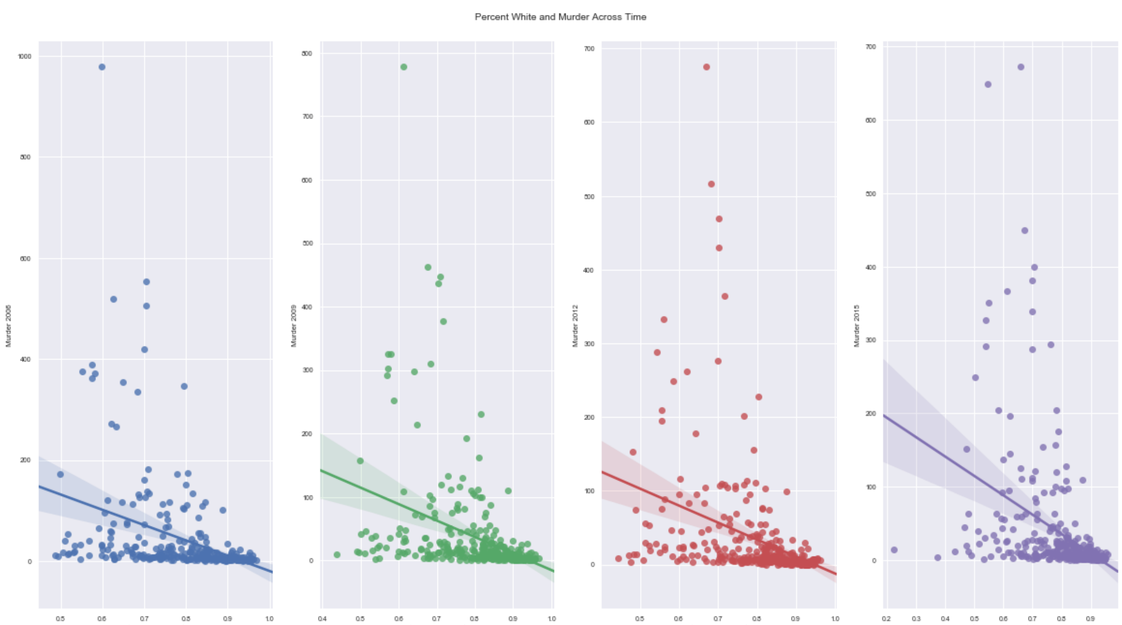

Murder 2012
poverty_12
murder_category
0
1
2
700
600
500
400
300
200
100
0
5
10
15
20
25
30
35



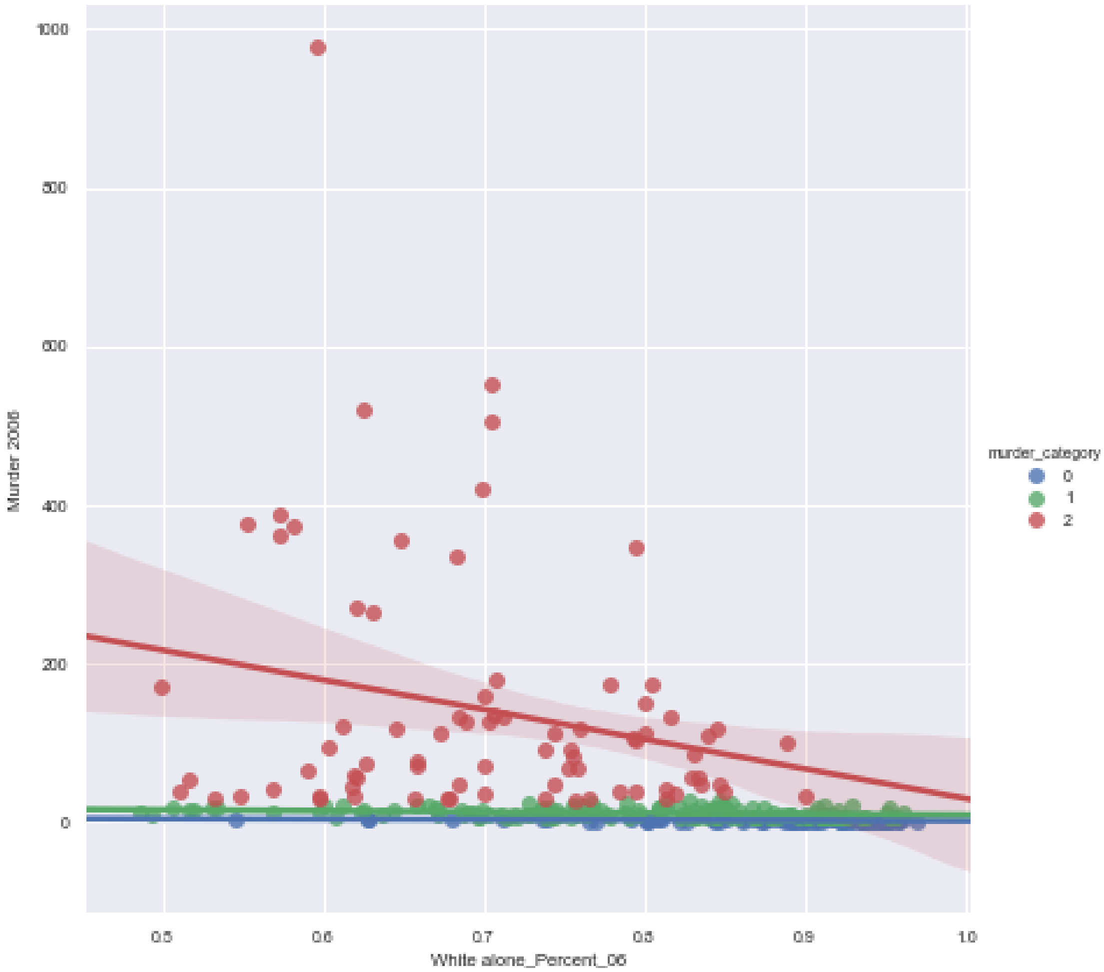

```
In [61]: feature_x_time('Poverty and Murder per 100,000 Across Time', 'poverty_', option = 2)
```

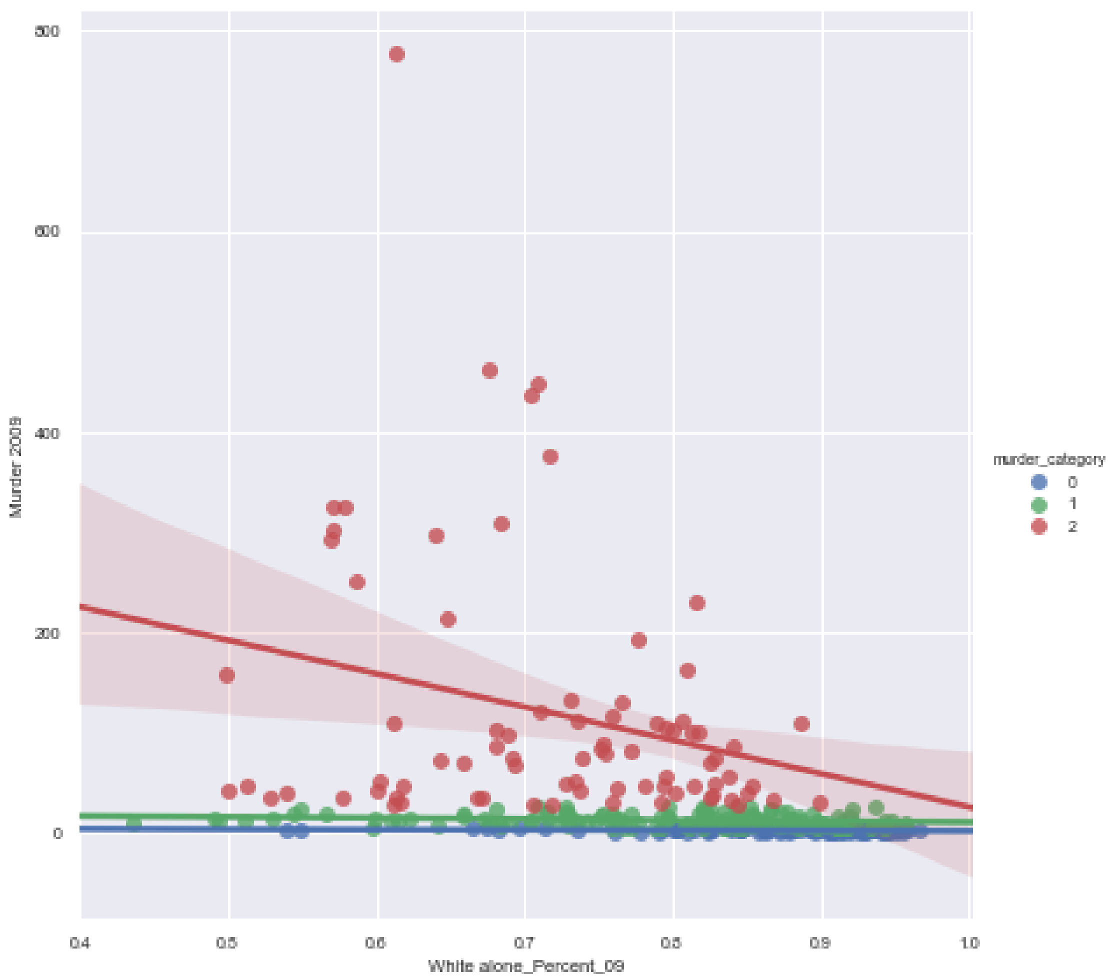



```
In [62]: feature_x_time('Percent White and Murder Across Time', 'White alone_Percent_')
```

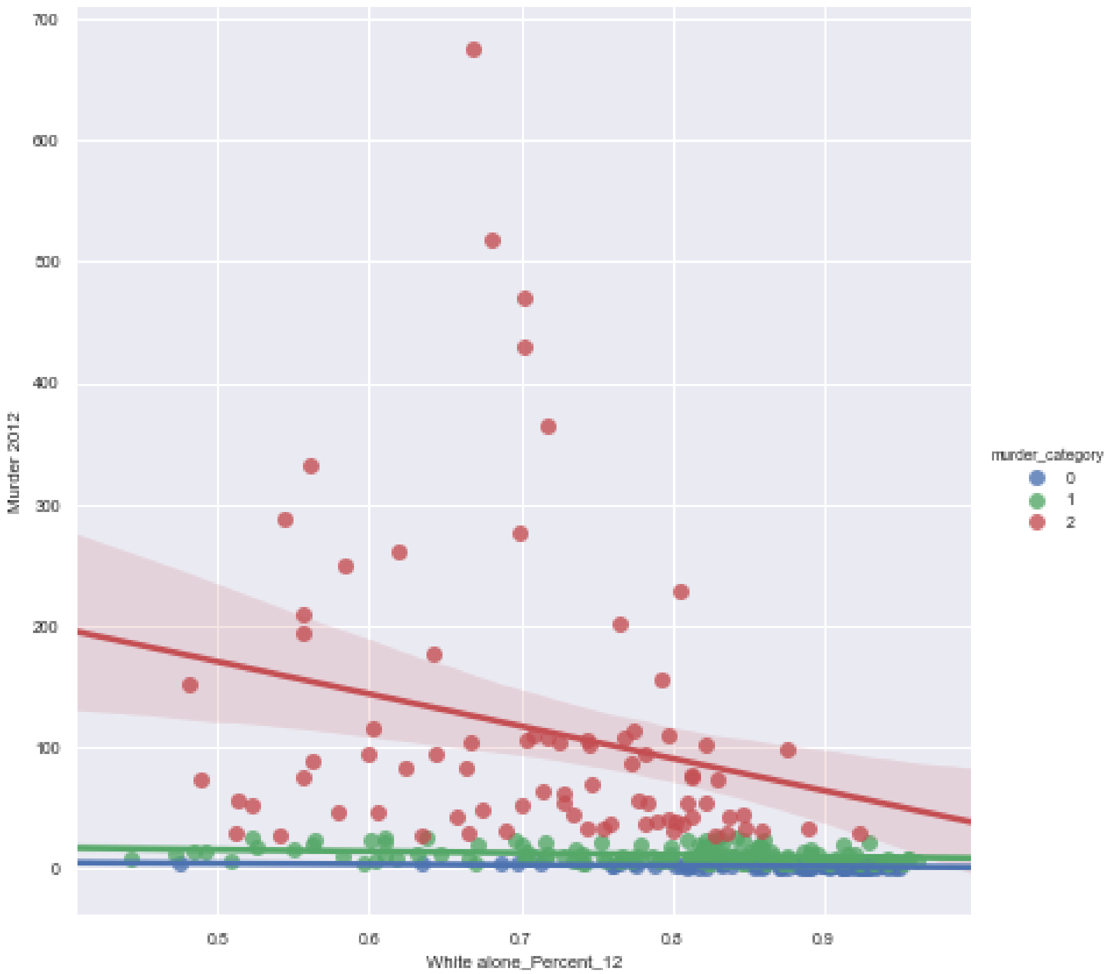



```
In [63]: feature_x_time('Percent White and Murder Across Time', 'White alone_Percent_', option =
```

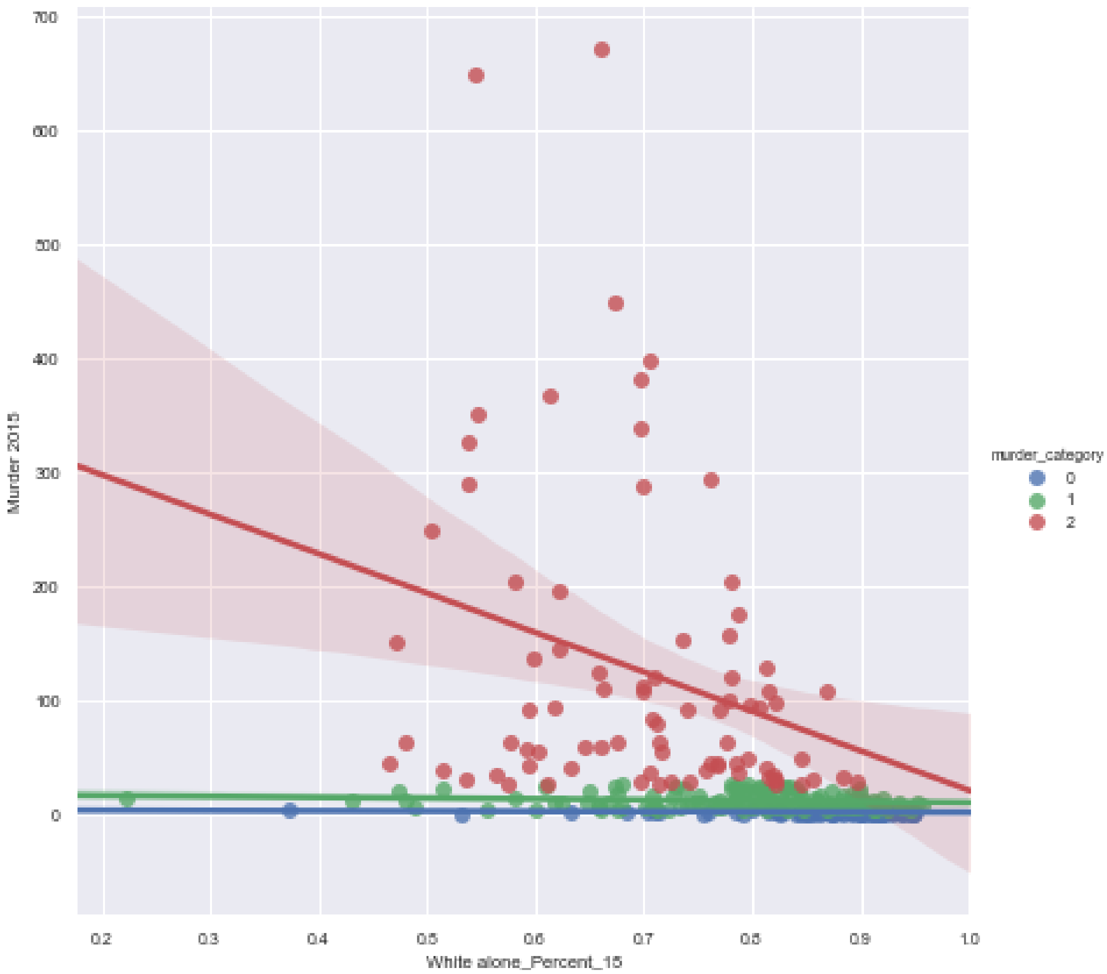

1000
800
600
400
200
0
Murder 2006
0.5
0.6
0.7
0.8
0.9
1.0
White alone_Percent_06
murder_category
0
1
2



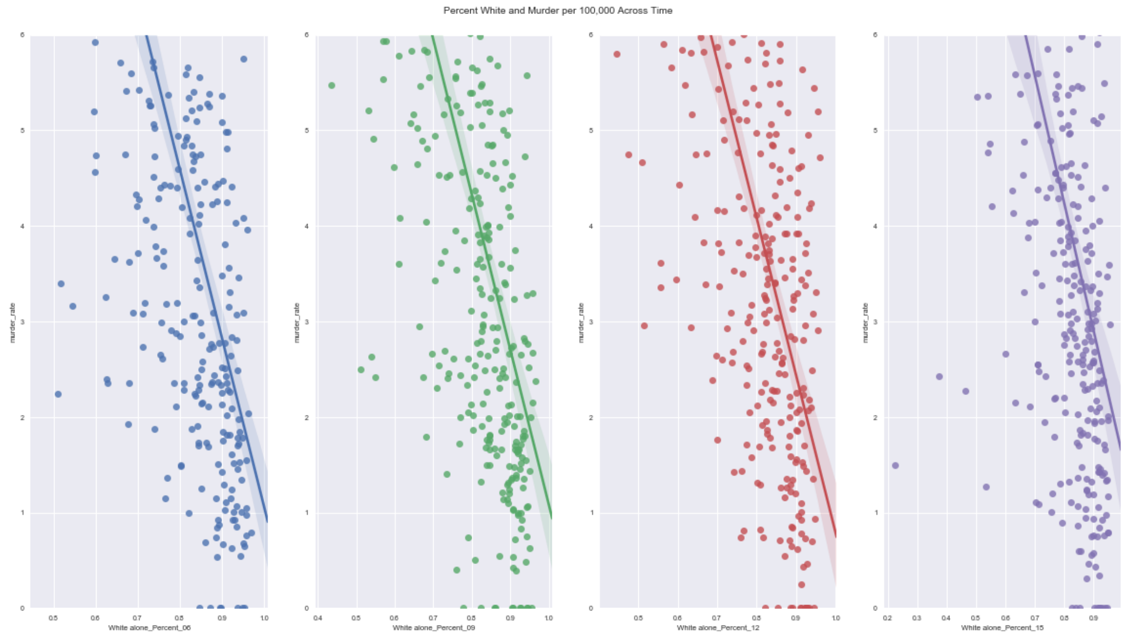
800
600
400
200
0
Murder 2009
0.4
0.5
0.6
0.7
0.8
0.9
1.0
White alone_Percent_09
murder_category
0
1
2



700
600
500
400
300
200
100
0
Murder 2012
0.5
0.6
0.7
0.8
0.9
White alone_Percent_12
murder_category
0
1
2

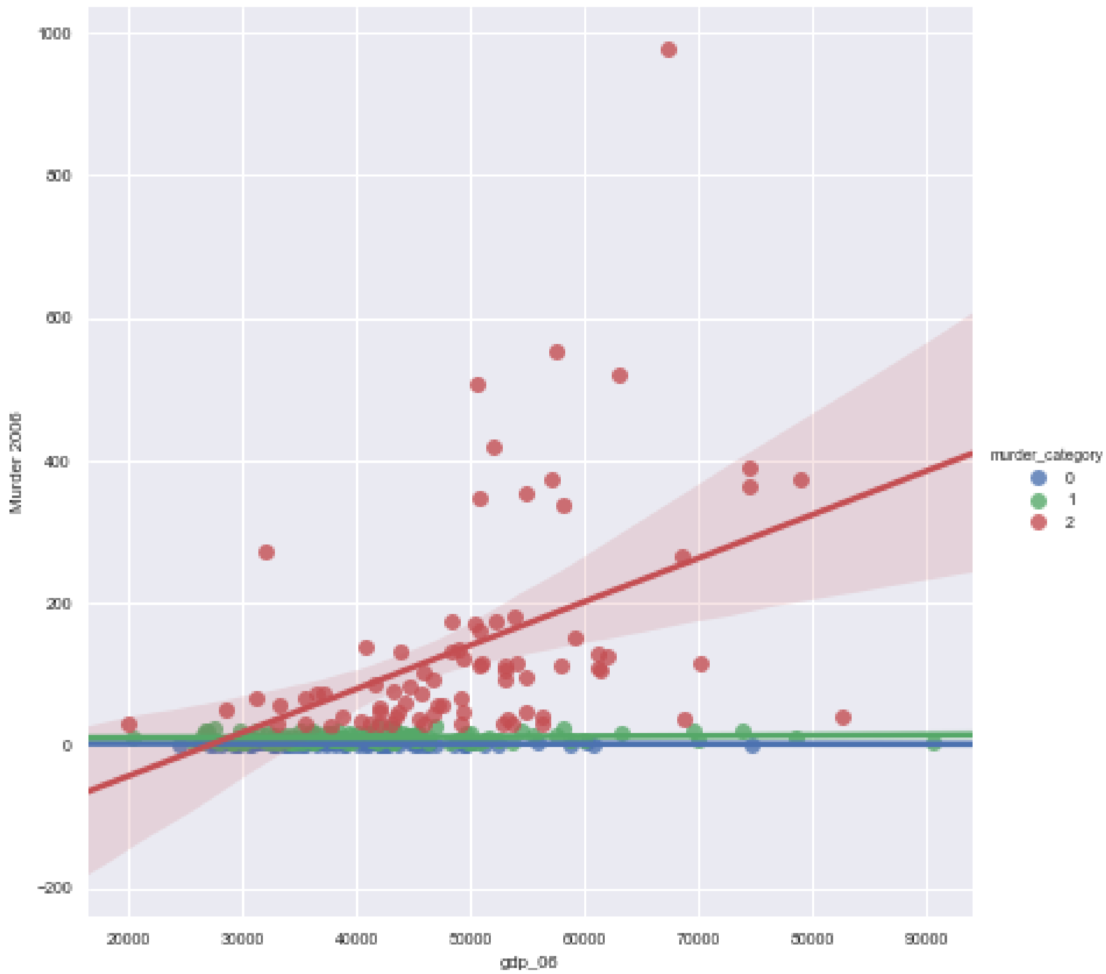


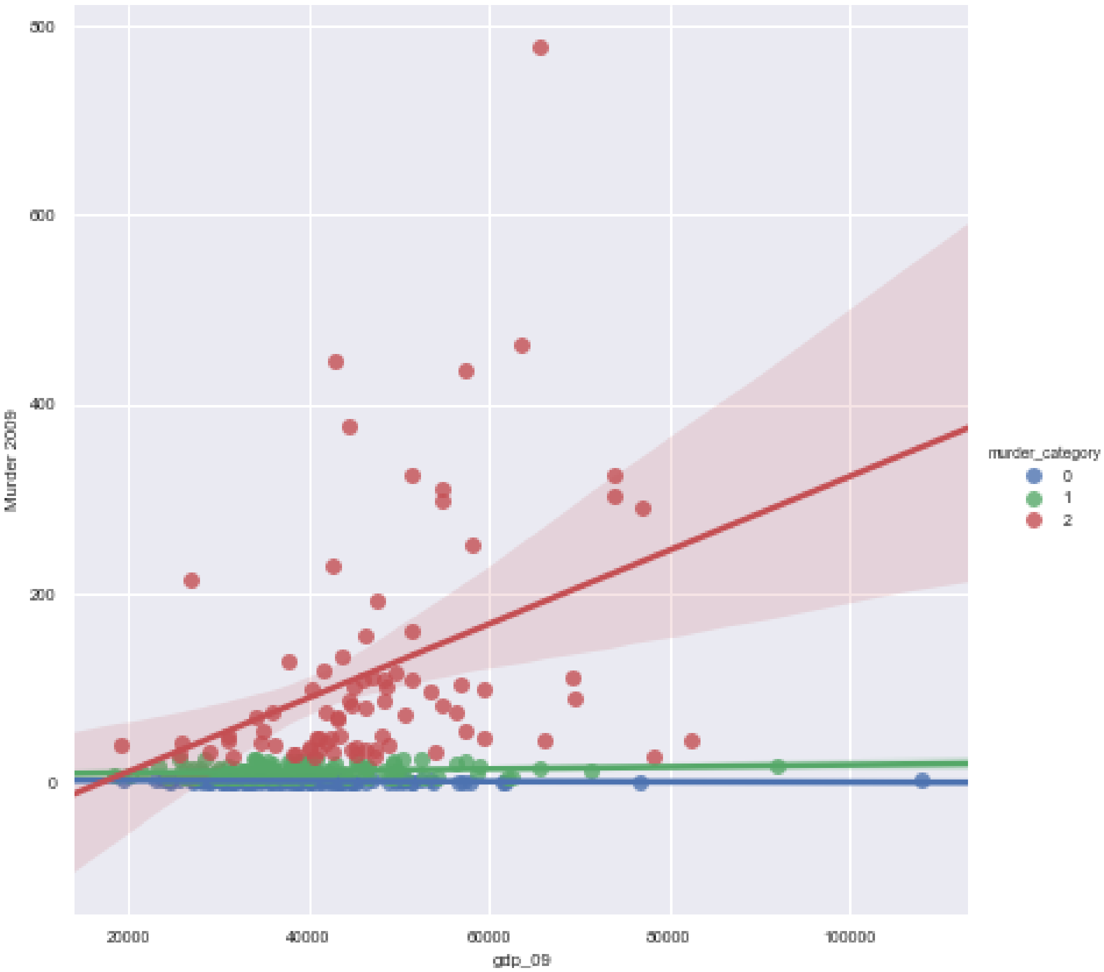

```
In [64]: feature_x_time('Percent White and Murder per 100,000 Across Time', 'White alone_Percent
```



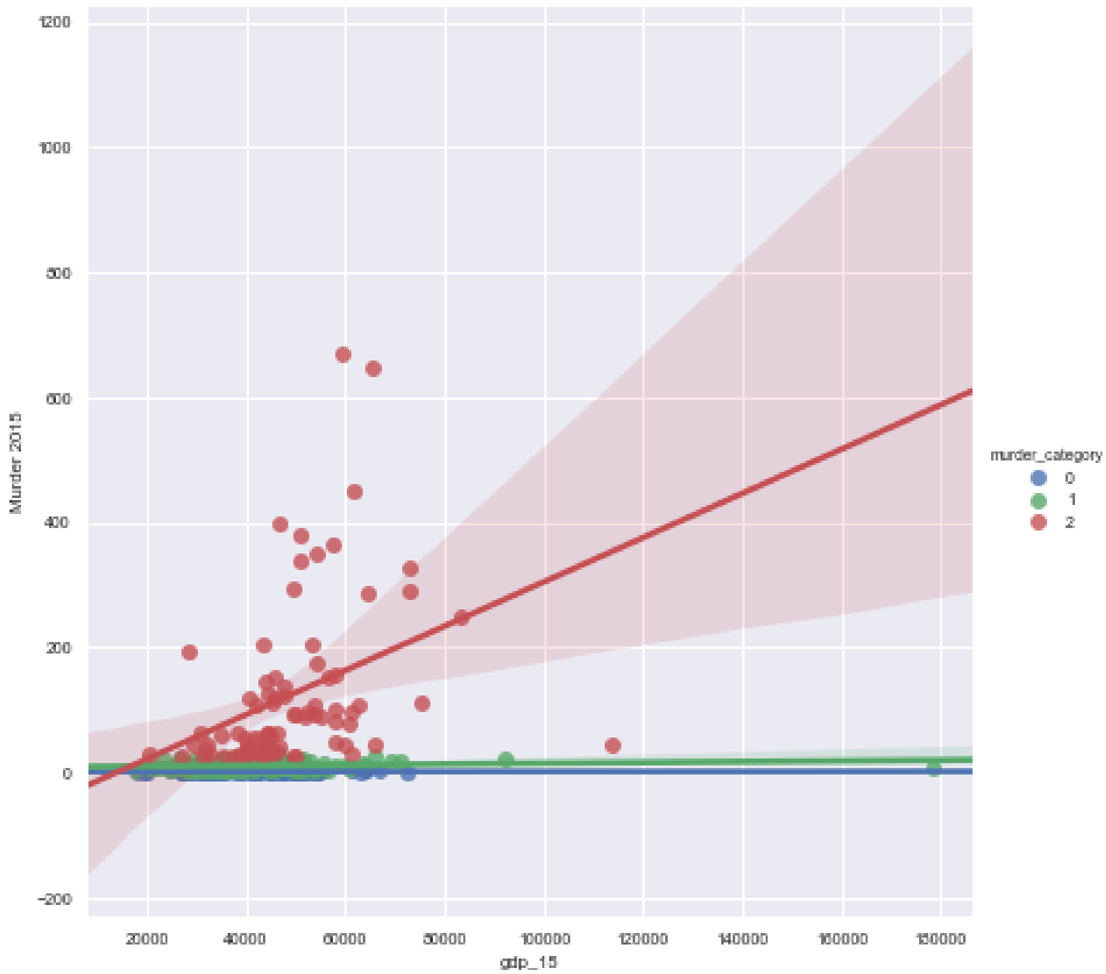

```
In [65]: feature_x_time("GDP and Murder Across Time", 'gdp_')
```


```
In [66]: feature_x_time("GDP and Murder Across Time", 'gdp_', option = 1)
```

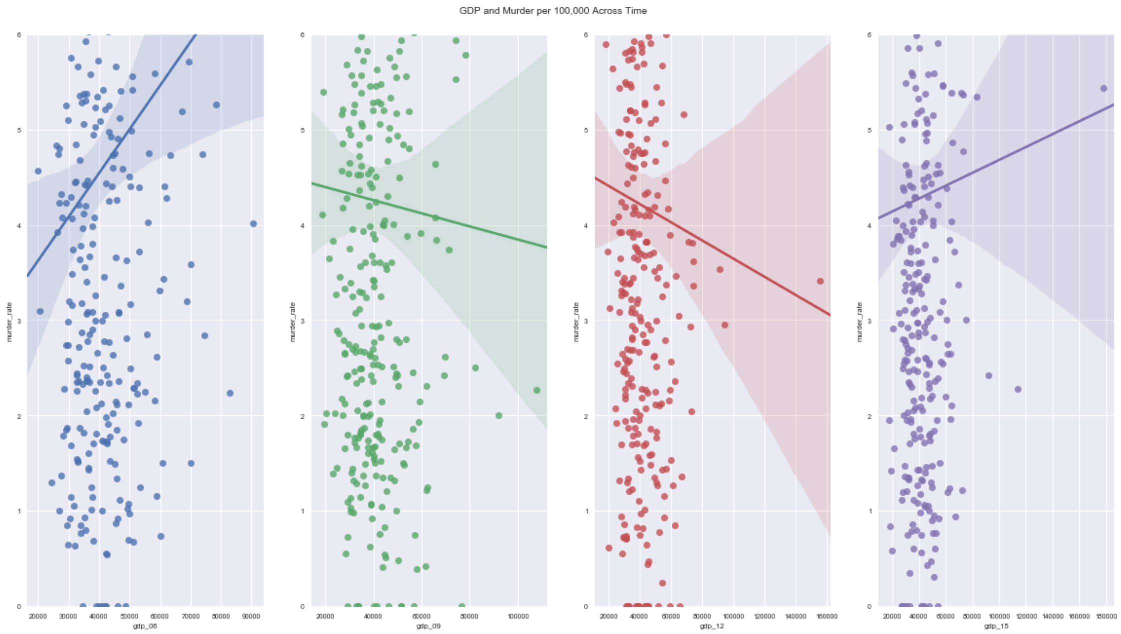

1000
800
600
400
200
0
−200
Murder 2006
20000
30000
40000
50000
60000
70000
80000
90000
gdp_06
murder_category
0
1
2


Murder 2009
800
600
400
200
0
20000
40000
60000
80000
100000
gdp_09
murder_category
0
1
2


Murder 2012
gdp_12
murder_category
0
1
2




```
In [67]: feature_x_time("GDP and Murder per 100,000 Across Time", 'gdp_', option = 2)
```

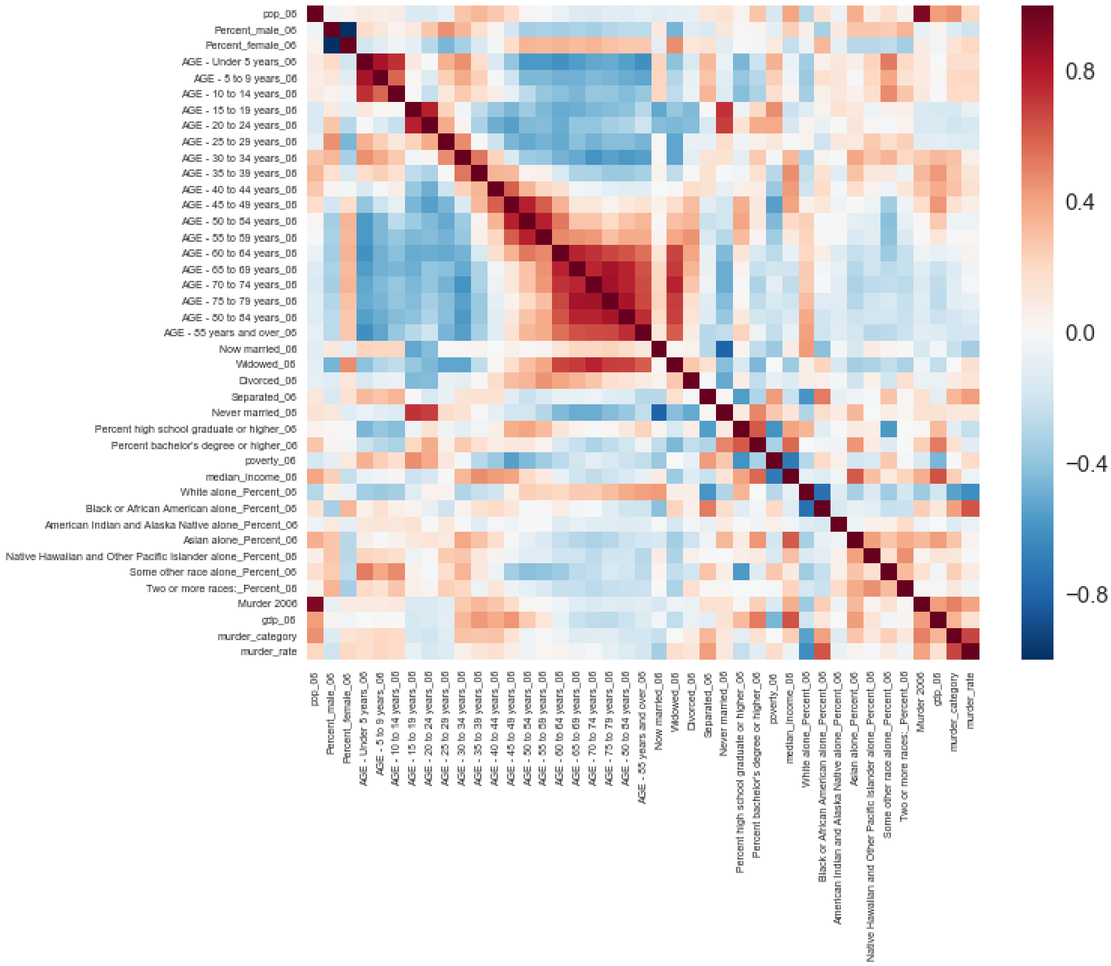


3.7 Feature-Feature Correlation

Looks like multicollinearity will be an issue. We will address this through feature selection

In [68]:
```
fig, ax = plt.subplots(figsize=(10, 8))

# corr heat map
sns.set(font_scale = 1.5)
sns.heatmap(dict_df_year[2006].corr(), ax = ax)
```

Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x11f506860>



4 Modeling

Before we do our model, lets first collapse the some of our age columns.

```
In [69]: # collapse age columns and drop specific columns
         for i in range(2006, 2017):
             dict_df_year[i]['under_18_' + '%02d' % (i - 2000)] = dict_df_year[i]['AGE - Under 5
             dict_df_year[i]['20_to_40_' + '%02d' % (i - 2000)] = dict_df_year[i]['AGE - 20 to 2
             dict_df_year[i]['40_to_60_' + '%02d' % (i - 2000)] = dict_df_year[i]['AGE - 40 to 4
             dict_df_year[i]['60_above_' + '%02d' % (i - 2000)] = dict_df_year[i]['AGE - 60 to 6
             dict_df_year[i] = dict_df_year[i].drop(['AGE - Under 5 years_' + '%02d' % (i - 2000
```

```
In [70]: dict_avg = {}

         for i in range(2006,2017):
             dict_avg[i] = pd.DataFrame.copy(dict_df_year[i])
```

In [71]:
```
# function that standarizes df with 2006 min, max and range and returns the x_train and
def preprocess(year, columns, y_name):

    # empty lists for column names
    columns_year = []
    columns_06 = []
    year_2 = '%02d' % (year - 2000)
    year_06 = '%02d' % 6

    # make columns names
    for column in columns:
        columns_year.append(column + year_2)
        columns_06.append(column + year_06)

    # df
    df = dict_df_year[year].dropna()

    # split
    x_train = df[columns_year]
    y_train = df[[y_name]]

    # scale df
    df_scale = dict_df_year[2006].dropna()

    # select columns
    columns_scale = df_scale[columns_06]
    x_columns = x_train.columns.tolist()

    # standardize
    scaler = StandardScaler().fit(columns_scale)
    x_train[x_columns] = scaler.transform(x_train)

    return x_train, y_train

# function that adds polynomial terms to x_train and x_test
# polfeatures
def more_terms(x_train, x_test, degree):
    columns = base_col
    poly = PolynomialFeatures(degree, interaction_only = False, include_bias = False)

    x_trainpoly = poly.fit_transform(x_train)
    x_testpoly = poly.fit_transform(x_test)
    feature = poly.get_feature_names(columns)
    x_train_poly = pd.DataFrame(x_trainpoly, columns = feature)
    x_test_poly = pd.DataFrame(x_testpoly, columns = feature)

    return x_train_poly, x_test_poly
```

We make a dict for all the features in x_year and all the murder counts over population in y_year

```
In [72]: # initialize dicts
         x_year = {}
         y_year = {}

         # features
         columns = ['Percent_male_' , 'under_18_', '20_to_40_', '40_to_60_', '60_above_', 'Now m


         # for each year scale and split and put into dict
         for year in range(2006, 2017):

             xyear, yyear = preprocess(year, columns, 'murder_rate')

             x_year[year] = xyear
             y_year[year] = yyear
```

4.1 Base Model (Ridge and Lasso)

We use the gender, age, and income as our basemodel. To account for time series, for each feature and year, we obtain a coefficent and use these to fit a model to each feature. We predict the coefficient for each feature, which gives us our model for 2016. We use RidgeCV and LassoCV to model 2016 data and make predictions on the murder/population.

```
In [73]: # col
         base_col = ['Percent_male_' , 'under_18_', '20_to_40_', '40_to_60_', '60_above_', 'medi

         # initialize dicts
         x_yearb = {}
         y_yearb = {}

         # split select feature for every year and fil dict
         for year in range(2006, 2017):

             xbyear, ybyear = preprocess(year, base_col, 'murder_rate')

             x_yearb[year] = xbyear
             y_yearb[year] = ybyear

In [74]: # initialize df
         coefficients_lassob = pd.DataFrame()
         coefficients_ridgeb = pd.DataFrame()

         # constants
         constant_lassob = []
         constant_ridgeb = []
```

```
    # add col names
    coefficients_lassob['columns'] = base_col
    coefficients_ridgeb['columns'] = base_col

    # get betas for every year using lasso cv and ridge cv
    for i in range(2006, 2016):
        lassob = LassoCV().fit(x_yearb[i], y_yearb[i].values.reshape(-1, 1))
        coefficients_lassob[i] = lassob.coef_

        ridgeb = RidgeCV().fit(x_yearb[i], y_yearb[i].values.reshape(-1, 1))
        coefficients_ridgeb[i] = ridgeb.coef_[0]

        # constants
        constant_lassob.append(lassob.intercept_)
        constant_ridgeb.append(ridgeb.intercept_)
```

In [75]:
```
# transpose and rename
coefficients_lassob = rename(coefficients_lassob.T)
coefficients_ridgeb = rename(coefficients_ridgeb.T)
```

In [76]:
```
# show
coefficients_lassob.head()
```

Out[76]:

	Percent_male_	under_18_	20_to_40_	40_to_60_	60_above_	median_income_
2006	-0.640029	0.882617	-0.108982	0.444397	-0	-0.0501331
2007	-0.434509	1.01228	-0.0344746	0.643091	-0	-0.379183
2008	-0.661512	0.87094	-0	0.24985	-0	-0.0917136
2009	-0.519636	0.733181	-0.000297521	0.354195	-0	-0.465388
2010	-0.654053	0.317147	-0	0.436378	-0.394344	-0.404777

In [77]:
```
# show
coefficients_ridgeb.head()
```

Out[77]:

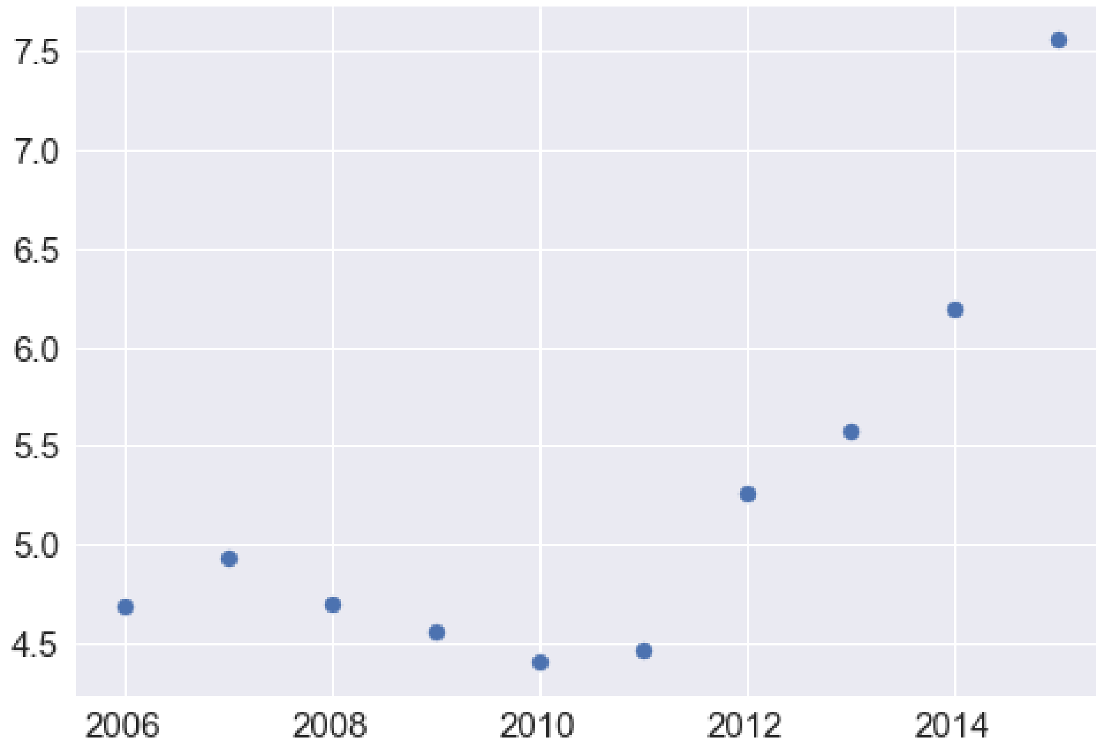
	Percent_male_	under_18_	20_to_40_	40_to_60_	60_above_	median_income_
2006	-0.635164	0.697911	-0.35722	0.346686	-0.313517	-0.124067
2007	-0.434678	0.643388	-0.400622	0.363601	-0.457374	-0.394092
2008	-0.665104	0.663585	-0.309884	0.142336	-0.397116	-0.180151
2009	-0.530811	0.524614	-0.263348	0.229722	-0.345614	-0.514892
2010	-0.663024	0.344533	-0.0204428	0.487956	-0.437737	-0.444311

4.1.1 Base Model Visualize

LassoCV

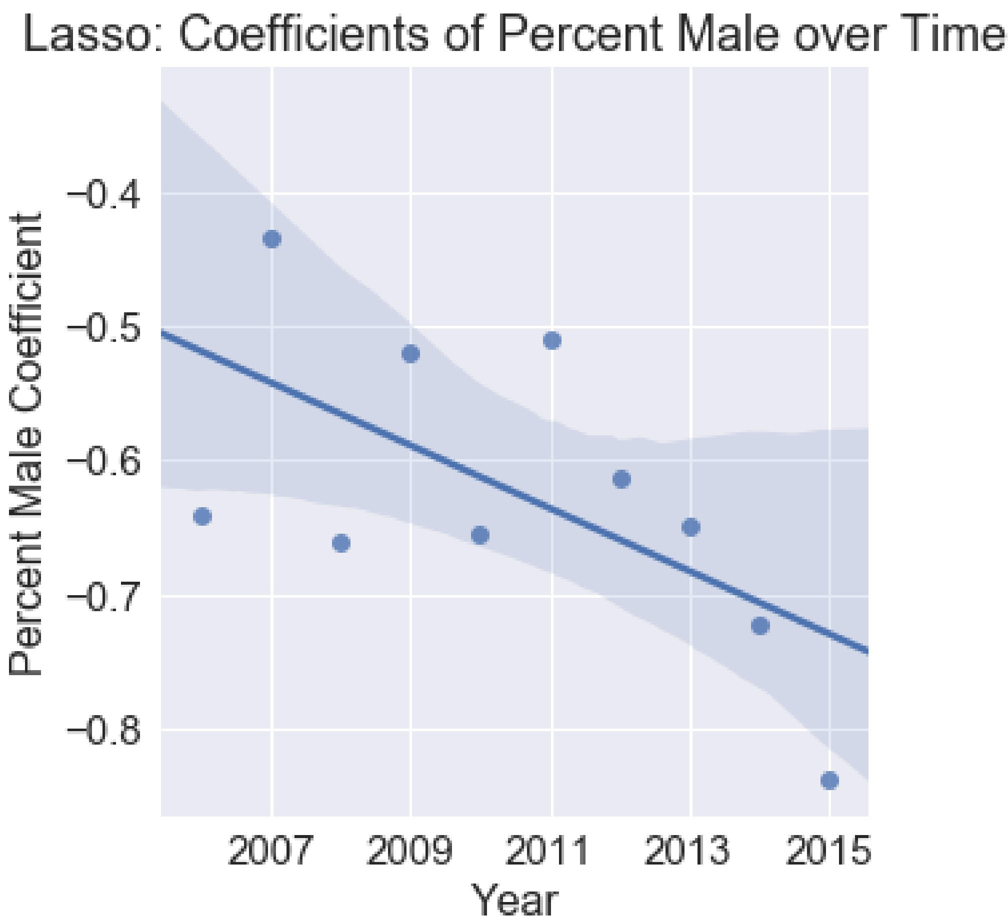
In [78]:
```
plt.scatter(np.arange(2006, 2016, 1), constant_lassob)
```

Out[78]:
```
<matplotlib.collections.PathCollection at 0x11ffee518>
```

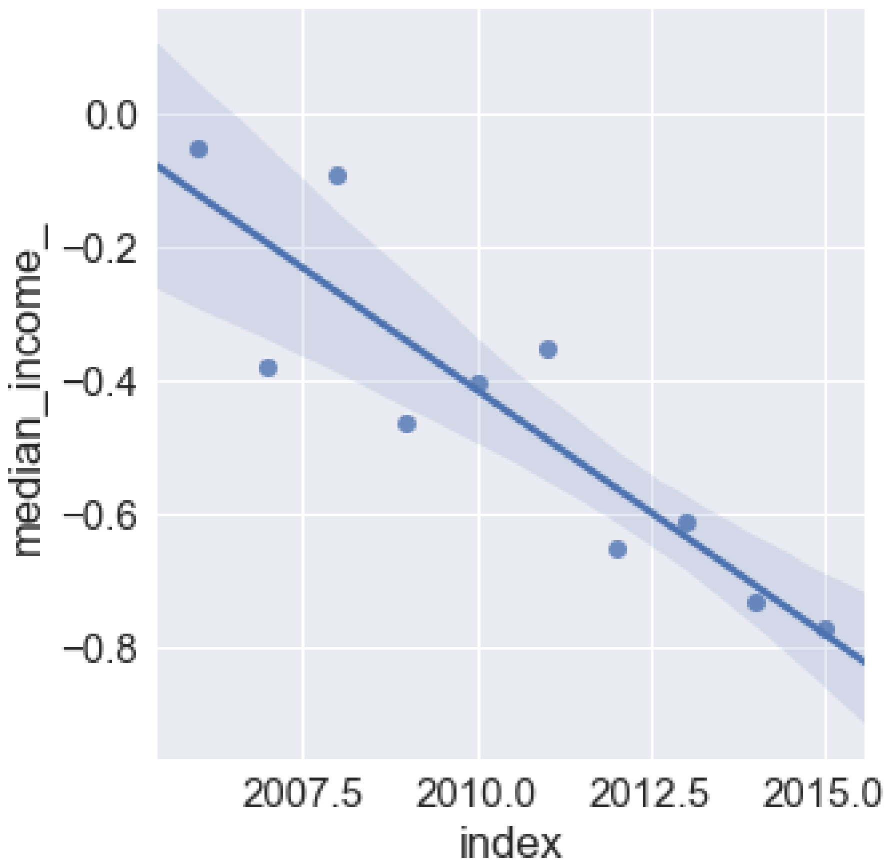


In [79]:
```
sns.lmplot(x = 'index', y = 'Percent_male_', data = coefficients_lassob.reset_index(),
plt.title("Lasso: Coefficients of Percent Male over Time")
plt.ylabel('Percent Male Coefficient', fontsize=16)
plt.xlabel('Year', fontsize=16)
plt.xticks([2007, 2009, 2011, 2013, 2015])
```

Out[79]:
```
([<matplotlib.axis.XTick at 0x1242be320>,
  <matplotlib.axis.XTick at 0x11f62e780>,
  <matplotlib.axis.XTick at 0x11f665780>,
  <matplotlib.axis.XTick at 0x1248bb3c8>,
  <matplotlib.axis.XTick at 0x123ee09b0>],
 <a list of 5 Text xticklabel objects>)
```

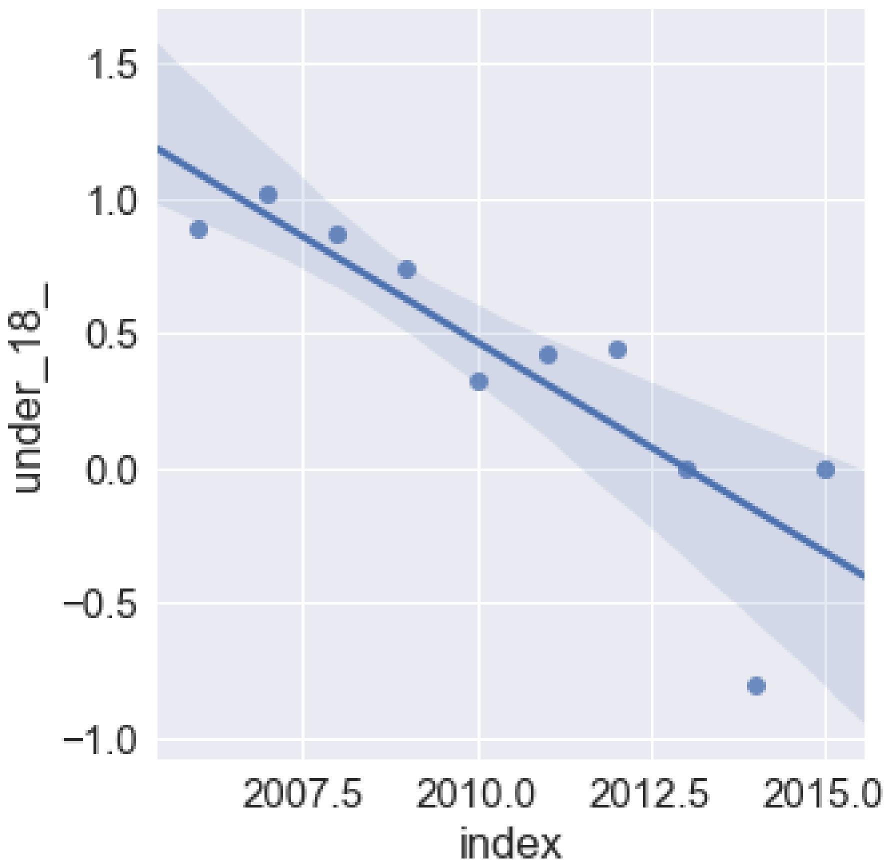



```
In [80]: sns.lmplot(x = 'index', y = 'median_income_', data= coefficients_lassob.reset_index(),

Out[80]: <seaborn.axisgrid.FacetGrid at 0x11d387b70>
```




```
In [81]: sns.lmplot(x = 'index', y = 'under_18_', data= coefficients_lassob.reset_index(), fit_r
```

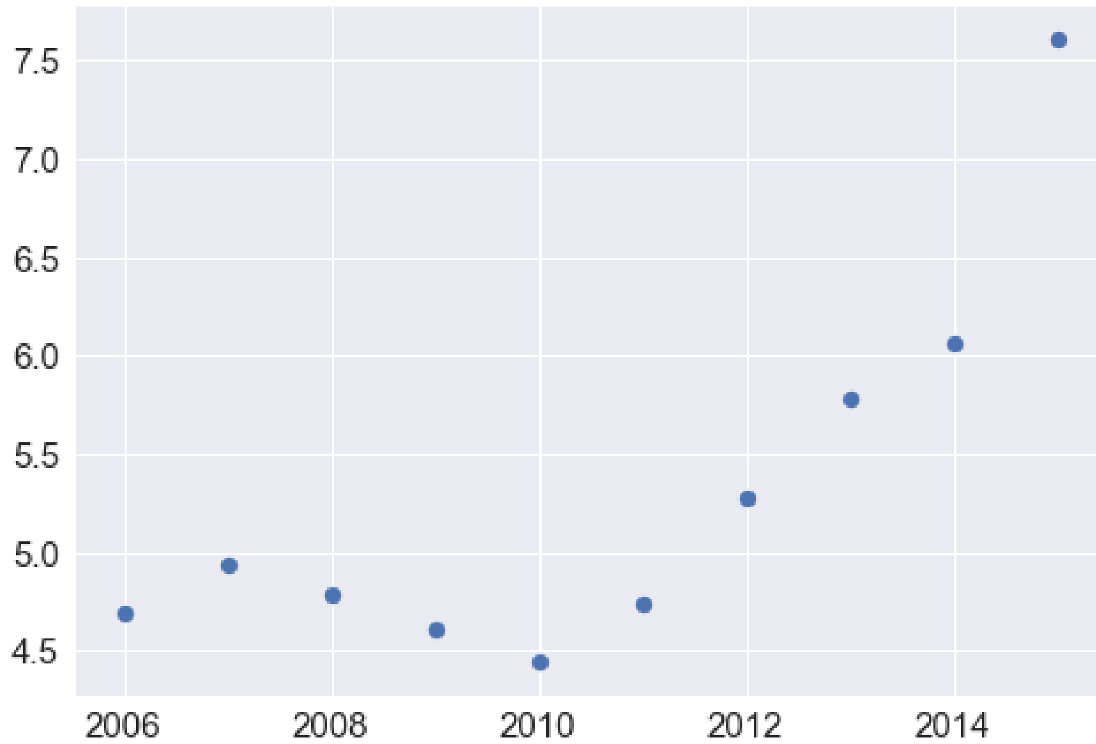
```
Out[81]: <seaborn.axisgrid.FacetGrid at 0x125253c88>
```



Ridge CV

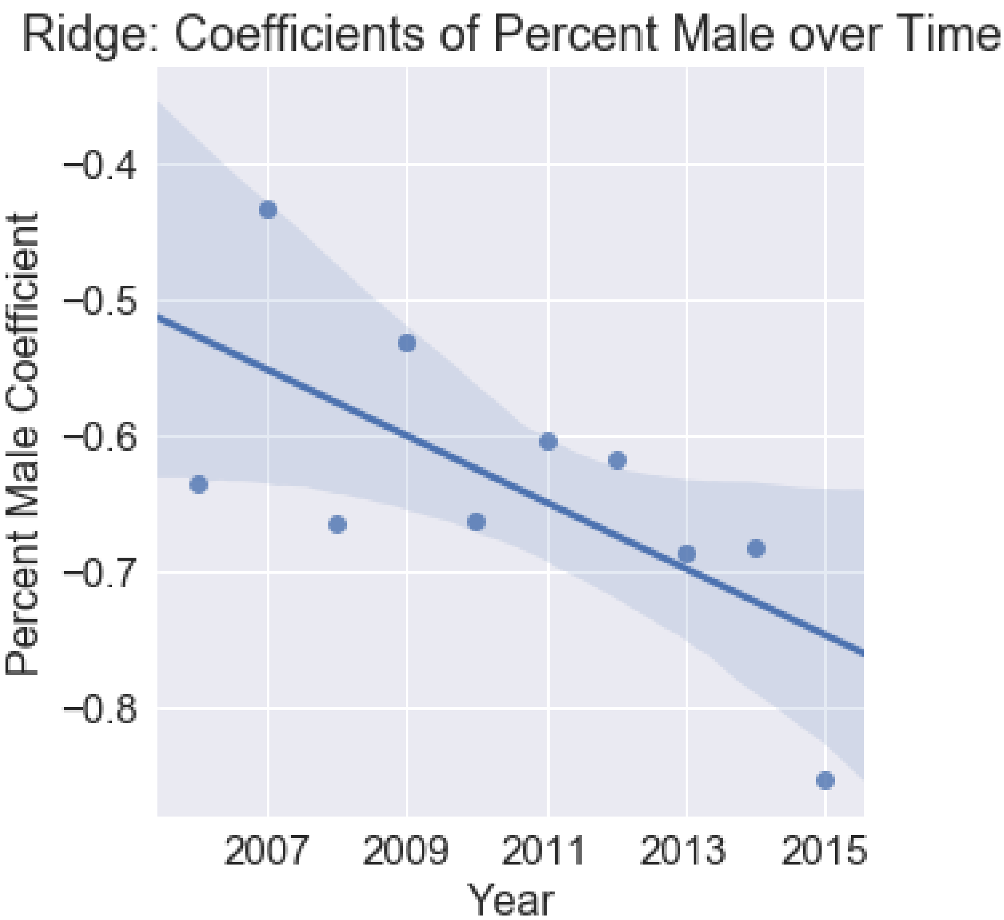
```
In [82]: plt.scatter(np.arange(2006, 2016, 1), constant_ridgeb)
```

```
Out[82]: <matplotlib.collections.PathCollection at 0x11ffcb470>
```




```
In [83]: sns.lmplot(x = 'index', y = 'Percent_male_', data = coefficients_ridgeb.reset_index(),
         plt.title("Ridge: Coefficients of Percent Male over Time")
         plt.ylabel('Percent Male Coefficient', fontsize=16)
         plt.xlabel('Year', fontsize=16)
         plt.xticks([2007, 2009, 2011, 2013, 2015])
```

```
Out[83]: ([<matplotlib.axis.XTick at 0x11e7b20b8>,
           <matplotlib.axis.XTick at 0x120d5efd0>,
           <matplotlib.axis.XTick at 0x123f44278>,
           <matplotlib.axis.XTick at 0x123f44f60>,
           <matplotlib.axis.XTick at 0x123f3ba58>],
          <a list of 5 Text xticklabel objects>)
```



In [84]: `sns.lmplot(x = 'index', y = 'Percent_male_', data= coefficients_ridgeb.reset_index(), f`

Out[84]: <seaborn.axisgrid.FacetGrid at 0x1246a8ba8>


```
In [85]: sns.lmplot(x = 'index', y = 'Percent_male_', data= coefficients_ridgeb.reset_index(), f
```

```
Out[85]: <seaborn.axisgrid.FacetGrid at 0x11e97a3c8>
```

4.1.2 Base Model: Predicting 2016 Beta

```
In [86]: coefficients_lassob
```

Out[86]:

	Percent_male_	under_18_	20_to_40_	40_to_60_	60_above_	median_income_
2006	-0.640029	0.882617	-0.108982	0.444397	-0	-0.0501331
2007	-0.434509	1.01228	-0.0344746	0.643091	-0	-0.379183
2008	-0.661512	0.87094	-0	0.24985	-0	-0.0917136
2009	-0.519636	0.733181	-0.000297521	0.354195	-0	-0.465388
2010	-0.654053	0.317147	-0	0.436378	-0.394344	-0.404777
2011	-0.510295	0.422349	-0.000609473	0.278687	-0	-0.352267
2012	-0.612182	0.443794	-0	0.80993	-0.453153	-0.650738
2013	-0.648021	0	-0	0.378217	-0.586899	-0.611886
2014	-0.722185	-0.802668	-0.196126	0.0961882	-1.42999	-0.733343
2015	-0.837259	-0	0	0.796936	-1.01884	-0.773814

```
In [87]: coefficients_ridgeb
```

Out[87]:

	Percent_male_	under_18_	20_to_40_	40_to_60_	60_above_	median_income_
2006	-0.635164	0.697911	-0.35722	0.346686	-0.313517	-0.124067

```
2007     -0.434678   0.643388  -0.400622  0.363601 -0.457374      -0.394092
2008     -0.665104   0.663585  -0.309884  0.142336 -0.397116      -0.180151
2009     -0.530811   0.524614  -0.263348  0.229722 -0.345614      -0.514892
2010     -0.663024   0.344533 -0.0204428  0.487956 -0.437737      -0.444311
2011     -0.603805   0.382543  -0.253286  0.420124 -0.422726      -0.560229
2012     -0.617557   0.315643  -0.161369  0.699032 -0.642465      -0.655928
2013     -0.686196   0.125453  0.0942125  0.606812  -0.57452      -0.685282
2014     -0.682826  -0.138663   0.362999  0.512965 -0.629696      -0.687292
2015     -0.853578  0.0652424   0.193498  0.923873 -0.881284      -0.800873
```

In [88]:
```
# our x values are the indexs (year 2006 to 2015)
x = coefficients_ridgeb.index.values

# initialize dataframes to store projected betas for 2016 model
model_lassob = pd.DataFrame()
model_lassob['columns'] = base_col

model_ridgeb = pd.DataFrame()
model_ridgeb['columns'] = base_col

# empty lists to fill
predict_lassob = []
predict_ridgeb = []

# for every column
for col in base_col:

    # fit a regression to the betas of each year
    regress_lassob = LinearRegression().fit(x.reshape(10, 1), coefficients_lassob[col])
    regress_ridgeb = LinearRegression().fit(x.reshape(10, 1), coefficients_ridgeb[col])

    # predict the beta of 2016
    predict_lassob.append(regress_lassob.predict(2016).tolist()[0])
    predict_ridgeb.append(regress_ridgeb.predict(2016).tolist()[0])

# model the constant
regress_lassocb = LinearRegression().fit(x.reshape(10,1), constant_lassob)
const_lassob = regress_lassocb.predict(2016)[0]
regress_ridgecb = LinearRegression().fit(x.reshape(10,1), constant_ridgeb)
const_ridgeb = regress_ridgecb.predict(2016)[0]

# add to df
model_lassob['coefficients'] = predict_lassob
model_ridgeb['coefficients'] = predict_ridgeb
```

In [89]:
```
# show
model_lassob
```

Out[89]:
```
           columns  coefficients
```

```
0   Percent_male_     -0.752476
1        under_18_     -0.470898
2        20_to_40_     -0.039064
3        40_to_60_      0.488650
4        60_above_     -1.157626
5   median_income_     -0.854546
```

In [90]:
```
# show
model_ridgeb
```

Out[90]:

```
           columns  coefficients
0   Percent_male_     -0.770915
1        under_18_     -0.119173
2        20_to_40_      0.301633
3        40_to_60_      0.803401
4        60_above_     -0.779495
5   median_income_     -0.878323
```

4.1.3 Base Model Performance

In [91]:
```
# column of 1
ones = np.ones((x_yearb[2016].shape[0], 1))

# add constant to coefficient list
ylassob = model_lassob['coefficients'].values.tolist()
ylassob.insert(0, const_lassob)

# add constant to coefficient list
yridgeb = model_ridgeb['coefficients'].values.tolist()
yridgeb.insert(0, const_ridgeb)

# predict
lassob_hat = np.dot(np.hstack((ones, x_yearb[2016])), np.array([ylassob]).T)
ridgeb_hat = np.dot(np.hstack((ones, x_yearb[2016])), np.array([yridgeb]).T)

# report
print('The R2 on the test set for using lasso to model the coefficients is', r2_score(y
print('The R2 on the test set for using ridge to model the coefficients is', r2_score(y
```

```
The R2 on the test set for using lasso to model the coefficients is 0.0581766303957
The R2 on the test set for using ridge to model the coefficients is 0.0493179030404
```

In [92]:
```
# start a results table
test_acc = pd.DataFrame(np.c_[r2_score(y_yearb[2016] , lassob_hat.ravel()),r2_score(y_y
```

4.2 Model 1 (Ridge and Lasso)

We use the same procedure we used for the base model but include more features.

```
In [93]: # make dataframe to fill
         coefficients_lasso = pd.DataFrame()
         coefficients_ridge = pd.DataFrame()

         constant_lasso = []
         constant_ridge = []


         # add a column of column names
         coefficients_lasso['columns'] = columns
         coefficients_ridge['columns'] = columns

         # for every year fit a lasso and ridge model but coef into a df
         for i in range(2006, 2016):

             lasso = LassoCV().fit(x_year[i], y_year[i].values.reshape(-1, 1))
             coefficients_lasso[i] = lasso.coef_

             ridge = RidgeCV().fit(x_year[i], y_year[i].values.reshape(-1, 1))
             coefficients_ridge[i] = ridge.coef_[0]

             # constants
             constant_lasso.append(lasso.intercept_)
             constant_ridge.append(ridge.intercept_)

In [94]: coefficients_lasso = rename(coefficients_lasso.T)
         coefficients_ridge = rename(coefficients_ridge.T)

In [95]: coefficients_lasso
```

Out[95]:

	Percent_male_	under_18_	20_to_40_	40_to_60_	60_above_	Now married_	\
2006	-0.0737585	0	-0.120371	-0	0	-0.310646	
2007	0.257747	0	-0.159392	-0	0.0311602	-0.0886804	
2008	-0	0.199566	-0.177468	-0	0	-0.249463	
2009	0	0	-0	0	-0	-0	
2010	-0	0	-0.170635	0	-0	-0.200519	
2011	0	0	-0.288664	0	0	-0	
2012	-0	0	-0.288608	0	-0	-0.170833	
2013	-0	0.311316	-0.20135	0	-0	-0.33857	
2014	-0	0	-0	0.0918426	-0.111397	-0.285857	
2015	-0.140188	0	-0	0	-0.121281	-0.0967096	

	Widowed_	Divorced_	Separated_	Never married_	...	poverty_	\
2006	0.0783093	0.260305	-0	0	...	0.00942778	
2007	0.421492	0.180766	0.265233	0	...	0.0635628	
2008	0.178018	0.274448	0	0	...	-0	
2009	0.301115	0.20434	0	0	...	0.109068	
2010	0	0.0416709	0	0	...	0	

```
2011          0   0.190487          0              0    ...      0.0897766
2012          0  0.0325993          0              0    ...       0.111312
2013          0    0.40593  -0.245987              0    ...      0.0919142
2014          0   0.197677          0              0    ...              0
2015          0  0.0941221         -0              0    ...              0

     median_income_ White alone_Percent_  \
2006             -0            -0.736414
2007       -0.18895             -1.12757
2008             -0             -1.04499
2009     -0.0271648            -0.978372
2010             -0            -0.670061
2011      -0.109286             -1.07249
2012   -0.000290382             -1.16685
2013             -0            -0.808767
2014       -0.04932            -0.610424
2015             -0            -0.898325

     Black or African American alone_Percent_  \
2006                                  1.30109
2007                                  1.37413
2008                                  1.06773
2009                                 0.810164
2010                                 0.893656
2011                                 0.889942
2012                                 0.774943
2013                                 0.871078
2014                                   1.0114
2015                                  1.03636

     American Indian and Alaska Native alone_Percent_ Asian alone_Percent_  \
2006                                       -0.0458542                   -0
2007                                         0.268435                   -0
2008                                               -0                   -0
2009                                               -0                   -0
2010                                               -0                    0
2011                                               -0                   -0
2012                                               -0                    0
2013                                                0             0.021704
2014                                               -0                   -0
2015                                                0           -0.0358721

     Native Hawaiian and Other Pacific Islander alone_Percent_  \
2006                                                  0
2007                                                 -0
2008                                         -0.0584644
2009                                                 -0
2010                                                 -0
```

```
2011                                                   0
2012                                                  -0
2013                                          -0.0942926
2014                                          -0.0464559
2015                                          -0.0821578

     Some other race alone_Percent_ Two or more races:_Percent_       gdp_
2006                       0.292345                          -0   0.418159
2007                              0                          -0   0.297181
2008                              0                          -0  0.0381334
2009                              0                           0         -0
2010                              0                   0.0586398          0
2011                              0                           0          0
2012                              0                           0          0
2013                             -0                          -0          0
2014                              0                -0.000114191          0
2015                              0                           0          0

[10 rows x 22 columns]
```

In [96]:
```
coefficients_ridge
```

Out[96]:
```
     Percent_male_  under_18_   20_to_40_   40_to_60_   60_above_  \
2006    -0.0747912   0.238735   -0.287168   -0.104337    0.147873
2007      0.403424   0.144366   -0.374893   -0.144828    0.204242
2008     0.0231769   0.405794   -0.350136   -0.140072   0.0393436
2009      0.153332   0.167023   -0.137943   0.0373835  -0.0340698
2010      0.098095   0.388321   -0.365263     0.15625  -0.0391539
2011      0.207791   0.313842   -0.639854  0.00415628    0.225246
2012      0.144069   0.468521   -0.647318    0.129458  0.00624488
2013    -0.0428088   0.420285   -0.401608  -0.0114577   -0.161821
2014    -0.0604756  0.0846521 -0.00468646    0.257999   -0.359619
2015     -0.433792   0.256249   0.0241171    0.141462   -0.373812

     Now married_   Widowed_ Divorced_ Separated_ Never married_    ...     \
2006    -0.371726   0.135581  0.420494  -0.180483        0.21671    ...
2007    -0.217077   0.357562  0.221052   0.339568      0.0142137    ...
2008    -0.353166   0.284775  0.389001 -0.0700646       0.122847    ...
2009   -0.0807763   0.489216  0.266589  -0.223994      0.0287585    ...
2010    -0.245115   0.261595  0.103557 -0.0503443       0.119954    ...
2011    -0.160869  -0.252273  0.234301  -0.164846       0.111794    ...
2012    -0.276079   0.011981  0.173533  -0.184547       0.204041    ...
2013    -0.397335  0.0842268  0.550506  -0.521681        0.15544    ...
2014    -0.294289   0.306807  0.402417 -0.0973602      0.0369984    ...
2015    -0.307489   0.312615  0.439992  -0.446619       0.103359    ...

       poverty_ median_income_ White alone_Percent_  \
2006  0.0663278      -0.038225             -1.00301
```

```
2007  0.0646792     -0.244484          -1.18221
2008  -0.305116     -0.208007          -1.04532
2009   0.197809     -0.146761         -0.979988
2010  0.0890927      -0.17026         -0.724182
2011  0.0383113     -0.427316          -1.04477
2012  0.0856101     -0.398206          -1.00022
2013   0.107768    -0.0111939         -0.813019
2014 -0.0426752     -0.162488         -0.777346
2015  -0.452774     -0.196361         -0.958669

     Black or African American alone_Percent_  \
2006                                  1.03808
2007                                  1.26932
2008                                  1.07242
2009                                 0.988476
2010                                 0.839109
2011                                  1.12364
2012                                  1.01552
2013                                 0.858185
2014                                 0.831626
2015                                 0.989301

     American Indian and Alaska Native alone_Percent_ Asian alone_Percent_  \
2006                                        -0.239006            -0.127095
2007                                         0.278785           -0.0687487
2008                                       -0.0468554           -0.0444688
2009                                        -0.115869            -0.140838
2010                                        -0.119499           0.00278037
2011                                        -0.107363            0.0475343
2012                                        -0.114439             0.176301
2013                                          0.27857             0.165308
2014                                          -0.1917           -0.0529405
2015                                         0.143204            -0.244905

     Native Hawaiian and Other Pacific Islander alone_Percent_  \
2006                                          0.0935778
2007                                         0.00269123
2008                                          -0.140197
2009                                          -0.057806
2010                                         -0.0341539
2011                                          0.0738702
2012                                         -0.0599582
2013                                         -0.0932266
2014                                          -0.042738
2015                                         -0.0791229

     Some other race alone_Percent_ Two or more races:_Percent_      gdp_
2006                       0.274821                   -0.112496  0.662554
```

```
2007                       -0.13859                 0.00955613  0.434763
2008                       0.128263                  0.0255226  0.182589
2009                       0.208286                   0.190136  0.136891
2010                      -0.134649                   0.254433  0.167132
2011                    -0.00728836                  0.0476045  0.197833
2012                      0.0336246                    0.15784  0.173905
2013                      -0.201819                 -0.0851694  0.130449
2014                       0.130912                 -0.0468135  0.128606
2015                      0.0926911                   0.124646  0.294837

[10 rows x 22 columns]
```

4.2.1 Lasso Beta Visualization

In [97]:
```
plt.scatter(np.arange(2006, 2016, 1), constant_lasso)
```

Out[97]: <matplotlib.collections.PathCollection at 0x12531d550>

In [98]:
```
sns.lmplot(x = 'index', y = 'Percent_male_', data= coefficients_lasso.reset_index(), fi
```

Out[98]: <seaborn.axisgrid.FacetGrid at 0x1246b7780>


```
In [99]: sns.lmplot(x = 'index', y = "median_income_", data= coefficients_lasso.reset_index(), f

Out[99]: <seaborn.axisgrid.FacetGrid at 0x1242b5be0>
```


```
In [100]: sns.lmplot(x = 'index', y = "White alone_Percent_", data= coefficients_lasso.reset_ind
```

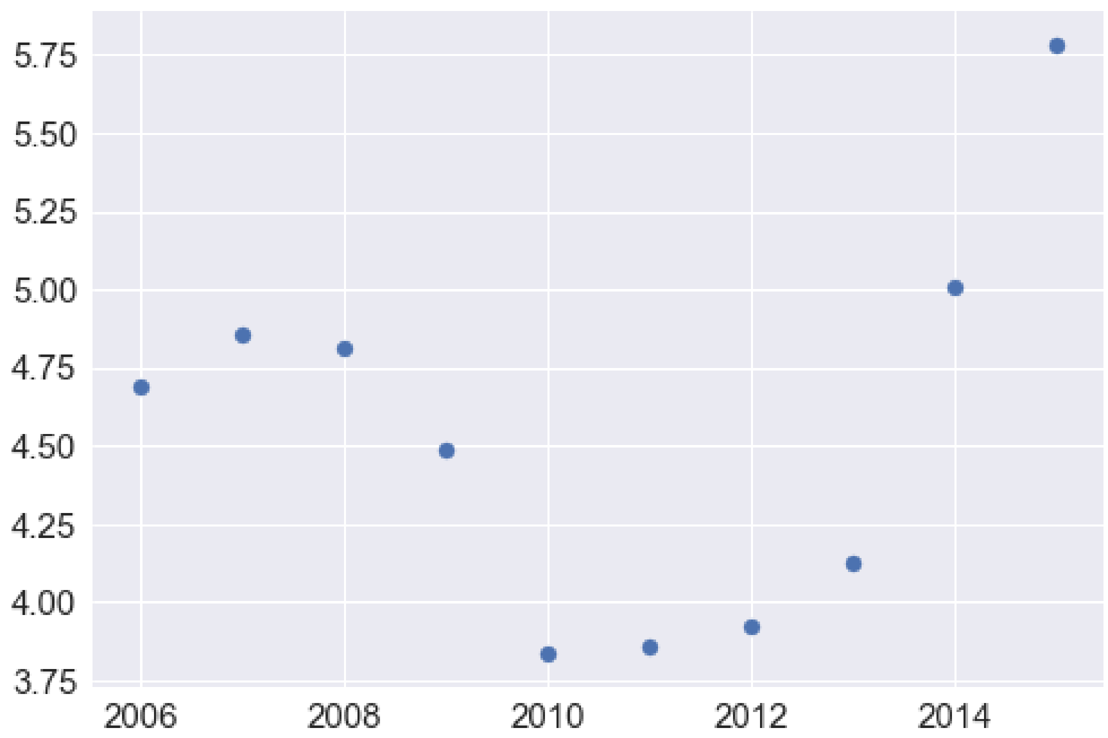
```
Out[100]: <seaborn.axisgrid.FacetGrid at 0x1252f2198>
```


```
In [101]: sns.lmplot(x = 'index', y = "gdp_", data= coefficients_lasso.reset_index(), fit_reg =
```

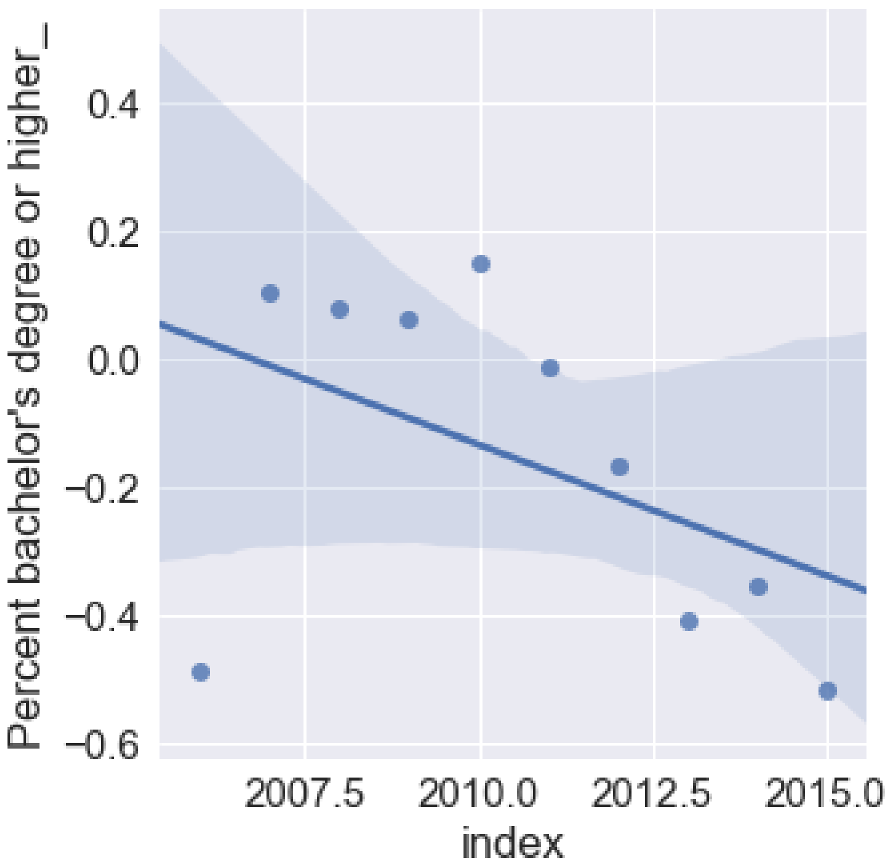
```
Out[101]: <seaborn.axisgrid.FacetGrid at 0x11f568518>
```

4.2.2 Ridge Beta Visualization

```
In [102]: plt.scatter(np.arange(2006, 2016, 1), constant_ridge)

Out[102]: <matplotlib.collections.PathCollection at 0x12004d7f0>
```

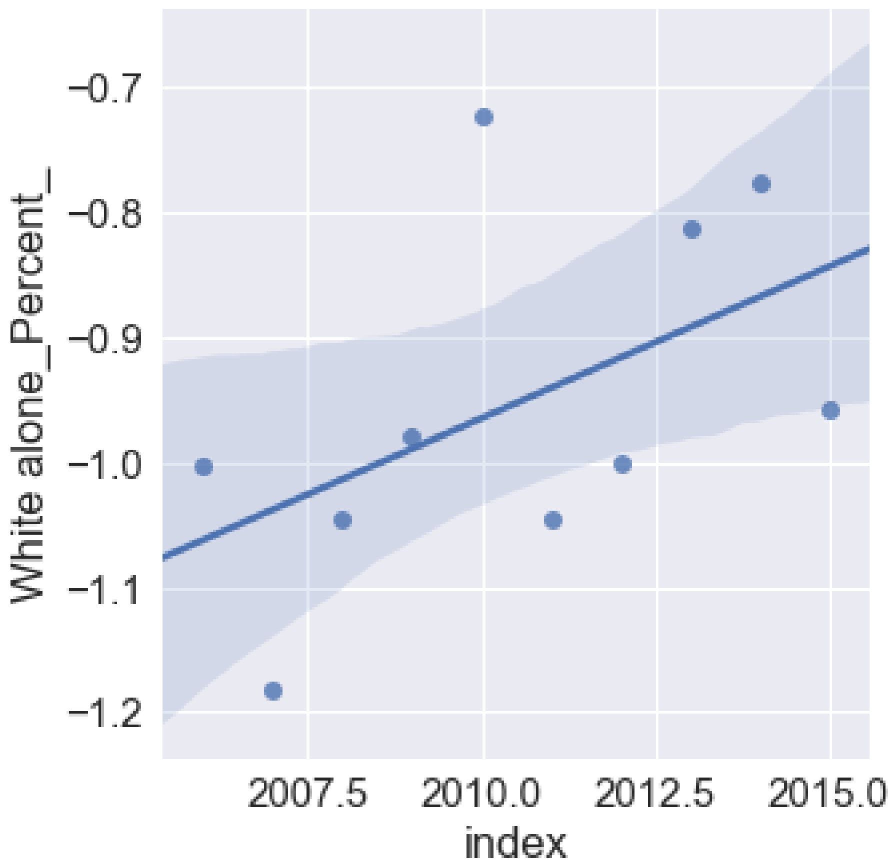



```
In [103]: sns.lmplot(x = 'index', y = "Percent bachelor's degree or higher_", data= coefficients

Out[103]: <seaborn.axisgrid.FacetGrid at 0x120d44320>
```




```
In [104]: sns.lmplot(x = 'index', y = "median_income_", data= coefficients_ridge.reset_index(),

Out[104]: <seaborn.axisgrid.FacetGrid at 0x11d065e80>
```


```
In [105]: sns.lmplot(x = 'index', y = "White alone_Percent_", data= coefficients_ridge.reset_ind

Out[105]: <seaborn.axisgrid.FacetGrid at 0x120abdc50>
```




```
In [106]: sns.lmplot(x = 'index', y = "gdp_", data= coefficients_ridge.reset_index(), fit_reg =
```

```
Out[106]: <seaborn.axisgrid.FacetGrid at 0x11f9be8d0>
```

4.3 Predicting 2016 Beta

```
In [107]: # initialize dataframes to store projected betas for 2016 model
          select_col = []
          select_col_16 = []

          model_lasso = pd.DataFrame()
          model_ridge = pd.DataFrame()

          # empty lists to fill
          predict_lasso = []
          predict_ridge = []

          # for every column
          for col in columns:
              if len(coefficients_lasso[col][coefficients_lasso[col].abs() > 0]) > 4:

                  select_col.append(col)
                  select_col_16.append(col + str(16))
```

```
        # fit a regression to the betas of each year
        regress_lasso = LinearRegression().fit(x.reshape(10, 1), coefficients_lasso[co
        regress_ridge = LinearRegression().fit(x.reshape(10, 1), coefficients_ridge[co

        # predict the beta of 2016
        predict_lasso.append(regress_lasso.predict(2016).tolist()[0])
        predict_ridge.append(regress_ridge.predict(2016).tolist()[0])

    # add columns
    model_lasso['columns'] = select_col
    model_ridge['columns'] = select_col

    # model the constant
    regress_lassoc = LinearRegression().fit(x.reshape(10,1), constant_lasso)
    const_lasso = regress_lassoc.predict(2016)[0]
    regress_ridgec = LinearRegression().fit(x.reshape(10,1), constant_ridge)
    const_ridge = regress_ridgec.predict(2016)[0]

    # add to df
    model_lasso['coefficients'] = predict_lasso
    model_ridge['coefficients'] = predict_ridge
```

In [108]: model_lasso

Out[108]:

	columns	coefficients
0	20_to_40_	-0.104122
1	Now married_	-0.181205
2	Divorced_	0.152026
3	Percent high school graduate or higher_	-0.071966
4	Percent bachelor's degree or higher_	-0.399958
5	poverty_	0.048383
6	median_income_	-0.005876
7	White alone_Percent_	-0.832224
8	Black or African American alone_Percent_	0.802572

In [109]: model_ridge

Out[109]:

	columns	coefficients
0	20_to_40_	-0.207377
1	Now married_	-0.293221
2	Divorced_	0.390282
3	Percent high school graduate or higher_	-0.365598
4	Percent bachelor's degree or higher_	-0.379171
5	poverty_	-0.139975
6	median_income_	-0.229550
7	White alone_Percent_	-0.819096
8	Black or African American alone_Percent_	0.862290

```
In [110]: ones = np.ones((x_year[2016].shape[0],1))

          # add constant to coefficient list
          ylasso = model_lasso['coefficients'].values.tolist()
          ylasso.insert(0, const_lasso)

          # add constant to coefficient list
          yridge = model_ridge['coefficients'].values.tolist()
          yridge.insert(0, const_ridge)

          # predict
          lasso_hat = np.dot(np.hstack((ones, x_year[2016][select_col_16])), np.array([ylasso]).
          ridge_hat = np.dot(np.hstack((ones, x_year[2016][select_col_16])), np.array([yridge]).

          # report
          print('The R2 on the test set for using lasso to model the coefficients is', r2_score(
          print('The R2 on the test set for using ridge to model the coefficients is', r2_score(
```

```
The R2 on the test set for using lasso to model the coefficients is 0.405715521583
The R2 on the test set for using ridge to model the coefficients is 0.444669689189
```

```
In [111]: test_acc['Lasso (base + extra features)'] = r2_score(y_year[2016] , lasso_hat.ravel())
          test_acc['Ridge (base + extra features)'] = r2_score(y_year[2016] , ridge_hat.ravel())
```

```
In [112]: test_acc
```

```
Out[112]:    Lasso (Base)  Ridge (Base)  Lasso (base + extra features)  \
          0      0.058177      0.049318                       0.405716

             Ridge (base + extra features)
          0                        0.44467
```

4.4 Average

In this method, we average over all years and take a subset of the averaged dataframe to train and test

```
In [113]: colnames = dict_df_year[2006].columns.str.replace('06', '').tolist()
```

```
In [114]: # msa df has all the msa names, good place to start search
          msa_list = msa_df['msa_name'].values
          df_avg = pd.DataFrame(columns = colnames)
```

```
In [115]: # iterate over msas, look at trends in years for each feature
          # average over these feature-trends
          for i in range(len(msa_list)):
              new_row = []
              for j in range((dict_avg[2006].shape[1])):
```

```
                var_list = []
                for k in range(10):
                    if dict_avg[2006 + k].loc[dict_avg[2006 + k]['msa_name'] == msa_list[i]].e
                        var_list.append(dict_avg[2006 + k].loc[dict_avg[2006 + k]['msa_name']
                    else:
                        var_list.append(np.nan)
                var_list = np.array(var_list)
                if j == 20:
                    avg = msa_list[i]
                elif j == 22:
                    avg = unique_id.loc[unique_id['msa_name'] == msa_list[i]]['ID'].values[0]
                else:
                    if i == 3 and j == 0:
                        print((var_list))
                        print(dict_avg[2006 + k].loc[dict_avg[2006 + k]['msa_name'] == msa_lis
                    avg = np.mean(var_list[~np.isnan(var_list)])
                new_row.append(avg)
            df_avg.loc[i] =new_row
```

```
[ 0.47601507  0.48071169         nan  0.47601042  0.477668    0.47350217
  0.47447732  0.47534826  0.46781698  0.46696434]
   Percent_male_15  Percent_female_15  AGE - 80 to 84 years_15  \
2         0.466964           0.533036                      1.9

   AGE - 85 years and over_15  Now married_15  Widowed_15  Divorced_15  \
2                        1.6            39.4         7.8         12.6

   Separated_15  Never married_15  Percent high school graduate or higher_15  \
2           5.2              35.0                                       82.3

      ...       Two or more races:_Percent_15    msa_name  Murder 2015     ID  \
2     ...                            0.017504  Albany, GA         12.0  10500

   gdp_15  murder_rate  under_18_15  20_to_40_15  40_to_60_15  60_above_15
2   29235     7.643458         28.5         24.4         26.3         20.9

[1 rows x 29 columns]
```

```
In [116]: df_avg = df_avg.dropna(axis = 0)
```

```
In [117]: base_col = ['Percent_male_' , 'under_18_', '20_to_40_', '40_to_60_', '60_above_', 'med

          # train/test split
          np.random.seed(9001)
          msk = np.random.randn(df_avg.shape[0]) < 0.7
          df_train = df_avg[msk]
          df_test = df_avg[~msk]
```

```
    # specific training/testing columns
    x_train = df_train[base_col]
    x_test = df_test[base_col]
    y_train = df_train['murder_rate']
    y_test = df_test['murder_rate']

    # standardizing
    scaler = StandardScaler().fit(x_train)
    x_train = scaler.transform(x_train)
    x_test = scaler.transform(x_test)
```

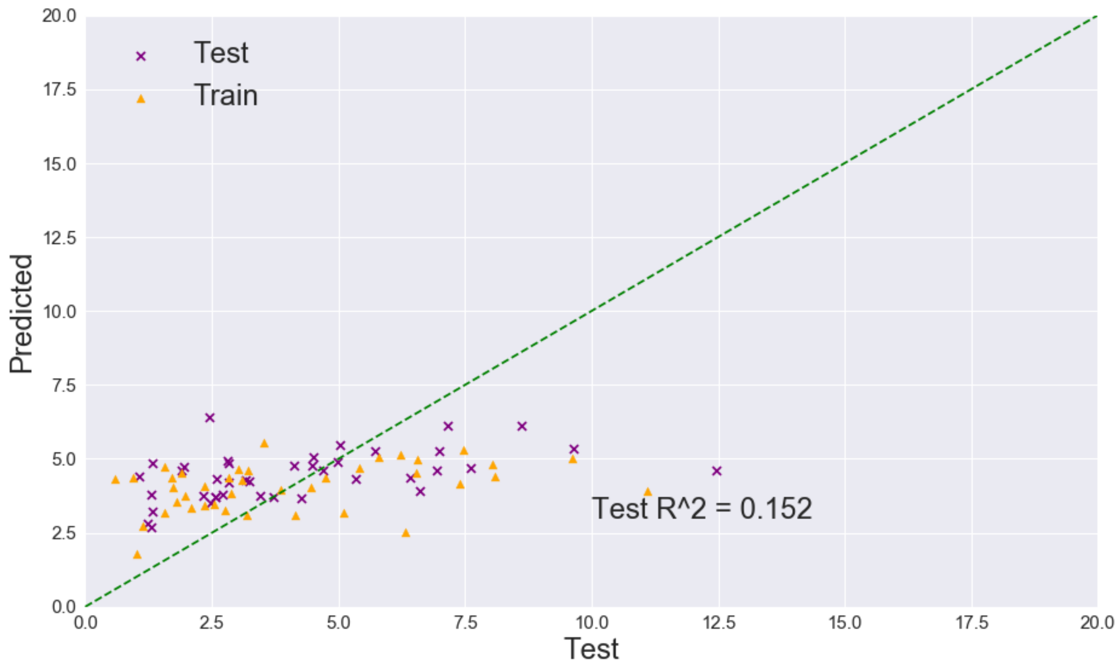
```
In [118]: lassoavg = LassoCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Lasso = %s'%(lassoavg.score(x_test, y_test)))
          ridgeavg = RidgeCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Ridge = %s'%(ridgeavg.score(x_test, y_test)))
```

```
Test R^2 with Lasso = 0.152184287169
Test R^2 with Ridge = 0.155698225619
```

```
In [119]: test_acc['Lasso (Base Average)'] = lassoavg.score(x_test, y_test)
          test_acc['Ridge (Base Average)'] = ridgeavg.score(x_test, y_test)
```

```
In [120]: plt.figure(figsize=(15,9))
          ypred = lassoavg.predict(x_test)[0:40]
          plt.scatter(y_test[0:40], ypred, c='purple', marker = 'x', label = 'Test')
          plt.scatter(y_train[0:40], lassoavg.predict(x_train)[0:40], c = 'orange', marker = '^'

          xvar = np.linspace(0,120,100)
          plt.text(10,3,'Test R^2 = ' + str(round(lassoavg.score(x_test,y_test),3)),fontsize=24)
          yvar = xvar
          plt.plot(xvar,yvar,'--',c='g')
          plt.xlabel('Test', fontsize = 24)
          plt.ylabel('Predicted',fontsize = 24)
          plt.legend(loc=2,prop={'size':24})


          plt.ylim(0, 20)
          plt.xlim(0, 20)
```

```
Out[120]: (0, 20)
```



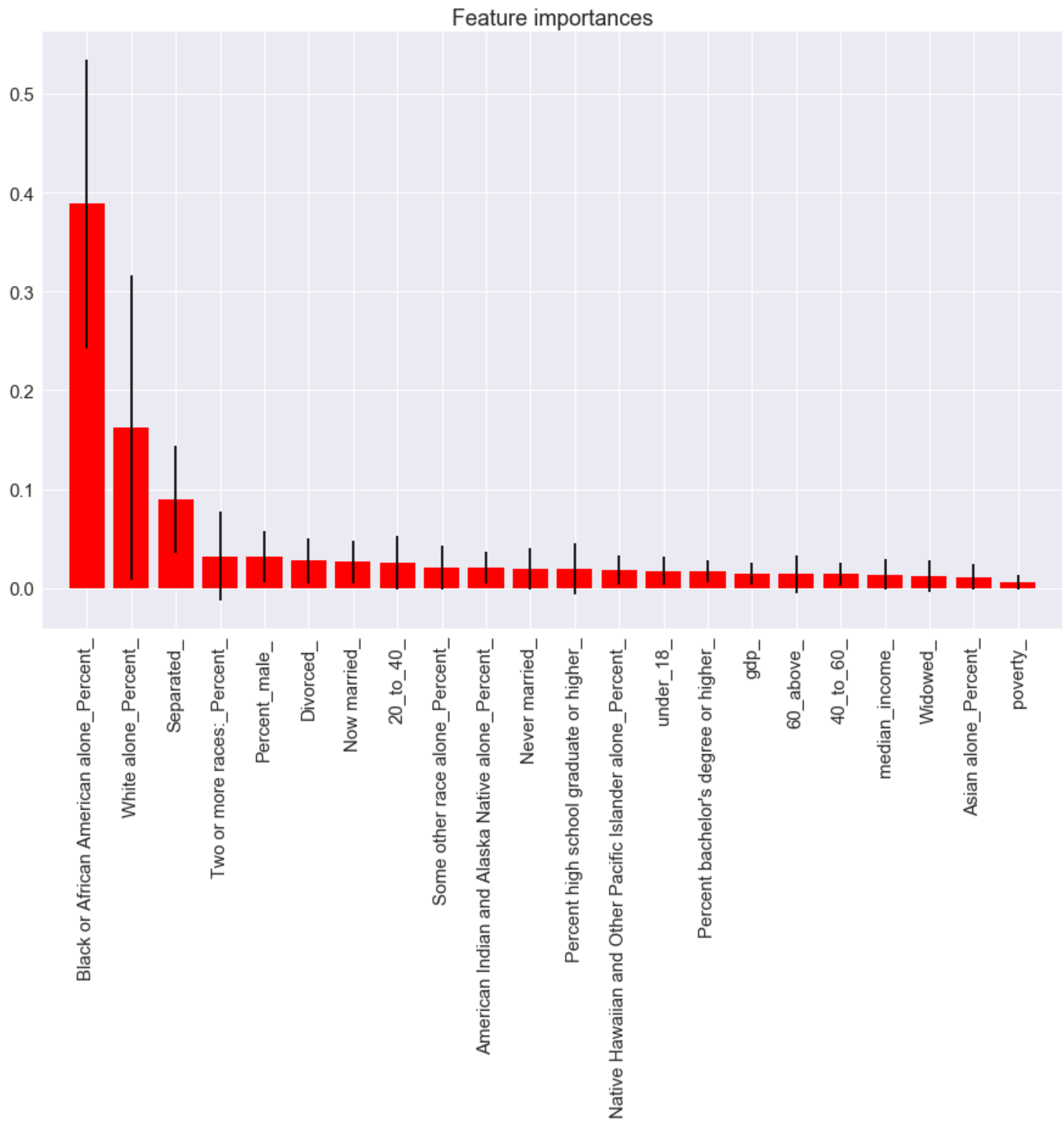

```
In [121]: base_col = ['Percent_male_', 'Now married_', 'Widowed_', 'Divorced_','Separated_', 'Ne

In [122]: # train/test split
          np.random.seed(9001)
          msk = np.random.randn(df_avg.shape[0]) < 0.7
          df_train = df_avg[msk]
          df_test = df_avg[~msk]

          # specific training/testing columns
          x_train = df_train[base_col]
          x_test = df_test[base_col]
          y_train = df_train['murder_rate']
          y_test = df_test['murder_rate']

          # standardizing
          scaler = StandardScaler().fit(x_train)
          x_train = scaler.transform(x_train)
          x_test = scaler.transform(x_test)

          lassoavg = LassoCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Lasso = %s'%(lassoavg.score(x_test, y_test)))
          ridgeavg = RidgeCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Ridge = %s'%(ridgeavg.score(x_test, y_test)))
          rfavg = RandomForestRegressor().fit(x_train, y_train)
          print('Test R^2 with RF = %s'%(rfavg.score(x_test, y_test)))
```

```
Test R^2 with Lasso = 0.604330356174
Test R^2 with Ridge = 0.639956016422
Test R^2 with RF = 0.595157101937
```

In [123]:
```python
importances = rfavg.feature_importances_
std = np.std([tree.feature_importances_ for tree in rfavg.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]

newlab = [base_col[i] for i in indices]

# Print the feature ranking
print("Feature ranking:")

for f in range(x_train.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

# Plot the feature importances of the forest
plt.figure(figsize=(15,9))
plt.title("Feature importances")
plt.bar(range(x_train.shape[1]), importances[indices],
       color="r", yerr=std[indices], align="center")
plt.xticks(range(x_train.shape[1]), newlab,rotation=90)
plt.xlim([-1, x_train.shape[1]])
plt.show()
```

```
Feature ranking:
1. feature 11 (0.388603)
2. feature 10 (0.162002)
3. feature 4 (0.089568)
4. feature 16 (0.032254)
5. feature 0 (0.031671)
6. feature 3 (0.027373)
7. feature 1 (0.026191)
8. feature 18 (0.025638)
9. feature 15 (0.020576)
10. feature 12 (0.020480)
11. feature 5 (0.019303)
12. feature 6 (0.019169)
13. feature 14 (0.018102)
14. feature 17 (0.017262)
15. feature 7 (0.017215)
16. feature 21 (0.014445)
17. feature 20 (0.013815)
18. feature 19 (0.013814)
19. feature 9 (0.013720)
20. feature 2 (0.011951)
```

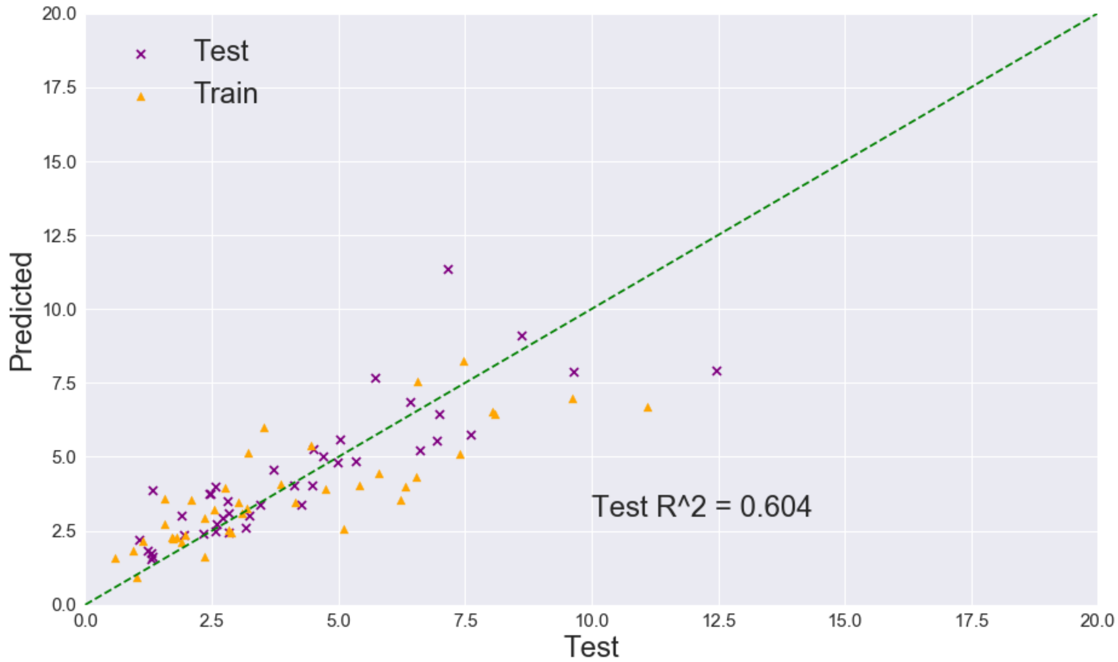
21. feature 13 (0.011079)
22. feature 8 (0.005770)




```
In [124]: test_acc['Lasso (base+add features average)'] = lassoavg.score(x_test, y_test)
          test_acc['Ridge (base+add features average)'] = ridgeavg.score(x_test, y_test)
          test_acc['RF (base+add features average)'] = rfavg.score(x_test, y_test)

In [125]: plt.figure(figsize=(15, 9))
          ypred = lassoavg.predict(x_test)[0:40]
          plt.scatter(y_test[0:40],ypred,c='purple',marker = 'x',label = 'Test')
          plt.scatter(y_train[0:40],lassoavg.predict(x_train)[0:40],c='orange',marker = '^',labe
```

```
xvar = np.linspace(0,20 ,10)
plt.text(10, 3, 'Test R^2 = ' + str(round(lassoavg.score(x_test, y_test), 3)),fontsize
yvar = xvar
plt.plot(xvar,yvar,'--',c='g')
plt.xlabel('Test',fontsize=24)
plt.ylabel('Predicted',fontsize=24)
plt.legend(loc = 2,prop = {'size':24})

plt.ylim(0, 20)
plt.xlim(0, 20)
```

Out[125]: (0, 20)

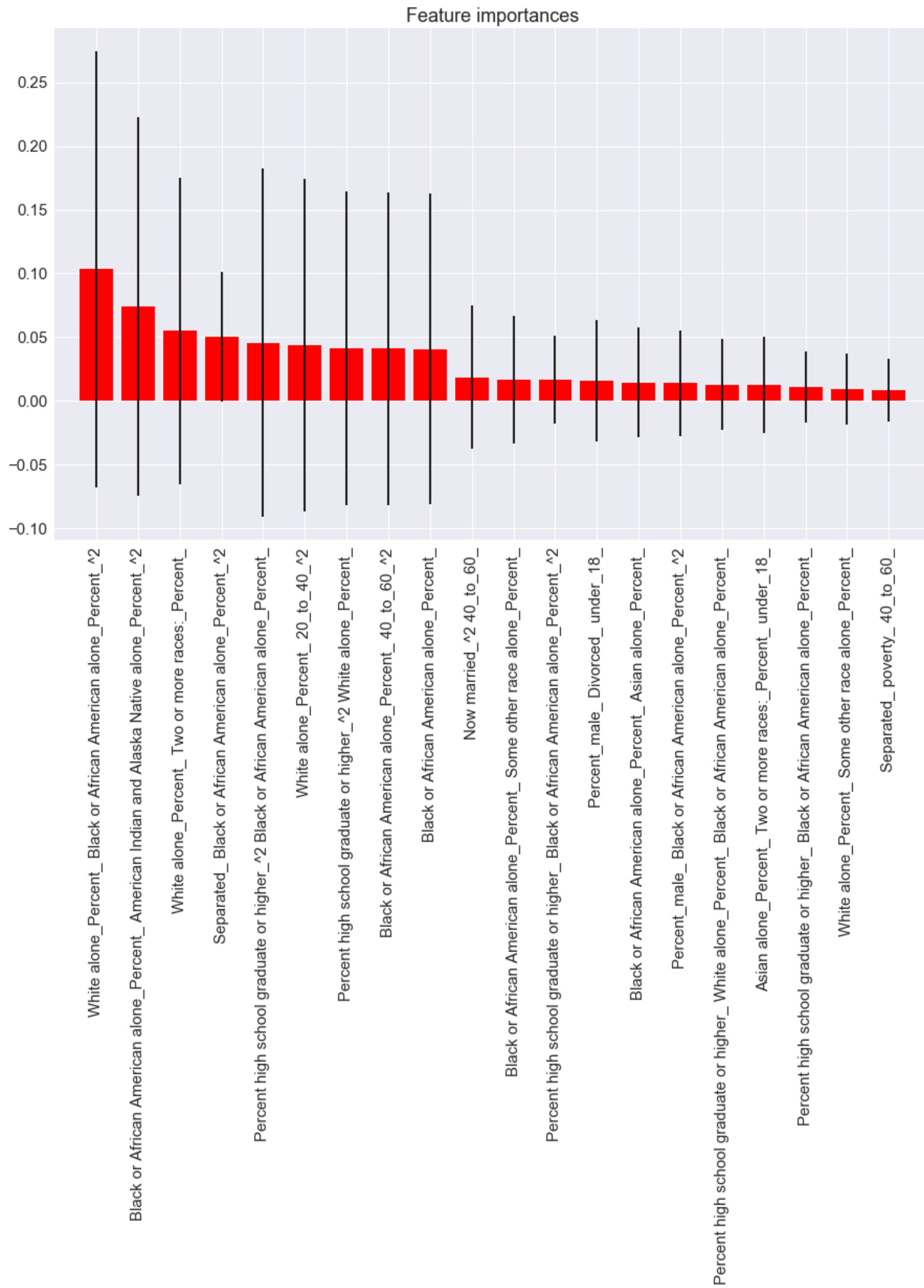


In [126]:
```
# train/test split
np.random.seed(9001)
msk = np.random.randn(df_avg.shape[0]) < 0.7
df_train = df_avg[msk]
df_test = df_avg[~msk]

# specific training/testing columns
x_train = df_train[base_col]
x_test = df_test[base_col]
y_train = df_train['murder_rate']
y_test = df_test['murder_rate']
```

```
# standardizing
scaler = StandardScaler().fit(x_train)
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)

from sklearn.preprocessing import PolynomialFeatures

x_train, x_test = more_terms(x_train, x_test, 3)

lassoavg = LassoCV(fit_intercept = True).fit(x_train, y_train)
print('Test R^2 with Lasso = %s'%(lassoavg.score(x_test, y_test)))
ridgeavg = RidgeCV(fit_intercept = True).fit(x_train, y_train)
print('Test R^2 with Ridge = %s'%(ridgeavg.score(x_test, y_test)))
rfavg = RandomForestRegressor().fit(x_train, y_train)
print('Test R^2 with RF = %s'%(rfavg.score(x_test, y_test)))
```

```
Test R^2 with Lasso = 0.456706649263
Test R^2 with Ridge = -22.021980383
Test R^2 with RF = 0.565370070829
```

```
In [127]: importances = rfavg.feature_importances_
          std = np.std([tree.feature_importances_ for tree in rfavg.estimators_],
                       axis=0)
          indices = np.argsort(importances)[::-1]

          newlab = [x_train.columns[i] for i in indices]

          # Plot the feature importances of the forest
          plt.figure(figsize=(15,9))
          plt.title("Feature importances")
          plt.bar(range(20), importances[indices][0:20],
                 color="r", yerr=std[indices][0:20], align="center")
          plt.xticks(range(20), newlab[0:20],rotation=90)
          plt.xlim([-1, 20])
          plt.show()
```

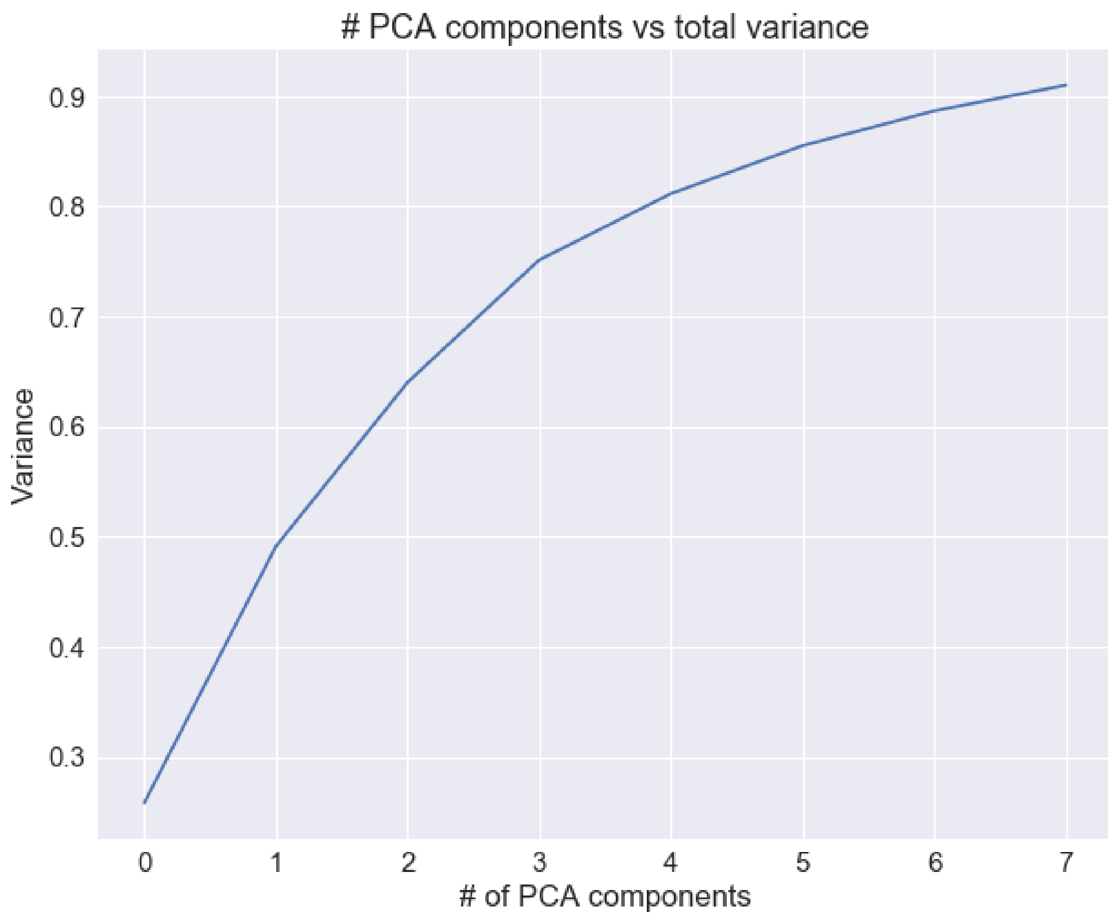



```
In [128]: test_acc['Lasso (complex features average)'] = lassoavg.score(x_test, y_test)
```

```
    test_acc['Ridge (complex features average)'] = ridgeavg.score(x_test, y_test)
    test_acc['RF (complex features average)'] = rfavg.score(x_test, y_test)
```

In [129]:
```
# train/test split
np.random.seed(9001)
msk = np.random.randn(df_avg.shape[0]) < 0.7
df_train = df_avg[msk]
df_test = df_avg[~msk]

# specific training/testing columns
x_train = df_train[base_col]
x_test = df_test[base_col]
y_train = df_train['murder_rate']
y_test = df_test['murder_rate']

# standardizing
scaler = MinMaxScaler().fit(x_train)
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)

pcavar = []
i = 1
while True:
    pca = PCA(n_components = i)
    pca.fit(x_train)
    pcavar.append(pca.explained_variance_ratio_.sum())
    if (pca.explained_variance_ratio_.sum()) >= 0.9:
        break
    i += 1

plt.figure(figsize = (10,8))
plt.plot(pcavar)
plt.title('# PCA components vs total variance')
plt.ylabel('Variance')
plt.xlabel('# of PCA components')
```

Out[129]:
```
<matplotlib.text.Text at 0x12375c748>
```




```
In [130]: pca = PCA(n_components = 7)
          pca.fit(x_train)
          x_train = pca.transform(x_train)
          x_test = pca.transform(x_test)

          lassoavg = LassoCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Lasso = %s'%(lassoavg.score(x_test, y_test)))
          ridgeavg = RidgeCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Ridge = %s'%(ridgeavg.score(x_test, y_test)))
          rfavg = RandomForestRegressor().fit(x_train, y_train)
          print('Test R^2 with RF = %s'%(rfavg.score(x_test, y_test)))
```

```
Test R^2 with Lasso = 0.57626498613
Test R^2 with Ridge = 0.577600708353
Test R^2 with RF = 0.529015422912
```

```
In [131]: test_acc['Lasso (PCA)'] = lassoavg.score(x_test, y_test)
          test_acc['Ridge (PCA)'] = ridgeavg.score(x_test, y_test)
          test_acc['RF (PCA)'] = rfavg.score(x_test, y_test)
```

5 2015 model

In this approach, we only use the 2015 dataset as train and the 2016 as test.

```
In [132]: base_col = ['Percent_male_' , 'under_18_', '20_to_40_', '40_to_60_', '60_above_', 'med
          dict15 = pd.DataFrame.copy(dict_df_year[2015])
          colnames = dict15.columns.str.replace('15', '').tolist()
          dict15.columns = colnames
          dict15 = dict15.dropna(axis = 0)

          dict16 = pd.DataFrame.copy(dict_df_year[2016])
          colnames = dict16.columns.str.replace('16', '').tolist()
          dict16.columns = colnames
          dict16 = dict16.dropna(axis = 0)
```

```
In [133]: x_train = dict15[base_col]
          y_train = dict15['murder_rate']
          x_test = dict16[base_col]
          y_test = dict16['murder_rate']

          scaler = StandardScaler().fit(x_train)
          x_train =scaler.transform(x_train)
          x_test = scaler.transform(x_test)

          lassoavg = LassoCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Lasso = %s'%(lassoavg.score(x_test, y_test)))
          ridgeavg = RidgeCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Ridge = %s'%(ridgeavg.score(x_test, y_test)))
          rfavg = RandomForestRegressor().fit(x_train, y_train)
          print('Test R^2 with RF = %s'%(rfavg.score(x_test, y_test)))
```

```
Test R^2 with Lasso = 0.184984007671
Test R^2 with Ridge = 0.185231612241
Test R^2 with RF = 0.382931023462
```

```
In [134]: test_acc['Lasso (base 2015)'] = lassoavg.score(x_test, y_test)
          test_acc['Ridge (base 2015)'] = ridgeavg.score(x_test, y_test)
          test_acc['RF (base 2015)'] = rfavg.score(x_test, y_test)
```

```
In [135]: base_col = ['Percent_male_', 'Now married_', 'Widowed_', 'Divorced_','Separated_', 'Ne

          x_train = dict15[base_col]
          y_train = dict15['murder_rate']
          x_test = dict16[base_col]
          y_test = dict16['murder_rate']

          scaler = StandardScaler().fit(x_train)
          x_train =scaler.transform(x_train)
```

```
x_test = scaler.transform(x_test)

lassoavg = LassoCV(fit_intercept = True).fit(x_train, y_train)
print('Test R^2 with Lasso = %s'%(lassoavg.score(x_test, y_test)))
ridgeavg = RidgeCV(fit_intercept = True).fit(x_train, y_train)
print('Test R^2 with Ridge = %s'%(ridgeavg.score(x_test, y_test)))
rfavg = RandomForestRegressor().fit(x_train, y_train)
print('Test R^2 with RF = %s'%(rfavg.score(x_test, y_test)))
```

```
Test R^2 with Lasso = 0.539690336936
Test R^2 with Ridge = 0.542384805987
Test R^2 with RF = 0.563916870639
```

```
In [136]: test_acc['Lasso (base+add 2015)'] = lassoavg.score(x_test, y_test)
          test_acc['Ridge (base+add 2015)'] = ridgeavg.score(x_test, y_test)
          test_acc['RF (base+add 2015)'] = rfavg.score(x_test, y_test)

In [137]: x_train = dict15[base_col]
          y_train = dict15['murder_rate']
          x_test = dict16[base_col]
          y_test = dict16['murder_rate']

          scaler = StandardScaler().fit(x_train)
          x_train =scaler.transform(x_train)
          x_test = scaler.transform(x_test)

          x_train, x_test = more_terms(x_train, x_test, 3)

          lassoavg = LassoCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Lasso = %s'%(lassoavg.score(x_test, y_test)))
          ridgeavg = RidgeCV(fit_intercept = True).fit(x_train, y_train)
          print('Test R^2 with Ridge = %s'%(ridgeavg.score(x_test, y_test)))
          rfavg = RandomForestRegressor().fit(x_train, y_train)
          print('Test R^2 with RF = %s'%(rfavg.score(x_test, y_test)))
```

```
Test R^2 with Lasso = 0.429372422981
Test R^2 with Ridge = -0.247138270863
Test R^2 with RF = 0.506115802568
```

```
In [138]: test_acc['Lasso (complex 2015)'] = lassoavg.score(x_test, y_test)
          test_acc['Ridge (complex 2015)'] = ridgeavg.score(x_test, y_test)
          test_acc['RF (complex 2015)'] = rfavg.score(x_test, y_test)

In [139]: test_acc.index = ['Test Accuracy']

In [140]: # summary table
          test_acc
```

Out[140]:
```
               Lasso (Base)  Ridge (Base)  Lasso (base + extra features)  \
Test Accuracy      0.058177      0.049318                       0.405716

               Ridge (base + extra features)  Lasso (Base Average)  \
Test Accuracy                        0.44467              0.152184

               Ridge (Base Average)  Lasso (base+add features average)  \
Test Accuracy              0.155698                            0.60433

               Ridge (base+add features average)  \
Test Accuracy                           0.639956

               RF (base+add features average)  \
Test Accuracy                        0.595157

               Lasso (complex features average)       ...          RF (PCA)  \
Test Accuracy                          0.456707       ...          0.529015

               Lasso (base 2015)  Ridge (base 2015)  RF (base 2015)  \
Test Accuracy           0.184984           0.185232        0.382931

               Lasso (base+add 2015)  Ridge (base+add 2015)  \
Test Accuracy                0.53969               0.542385

               RF (base+add 2015)  Lasso (complex 2015)  Ridge (complex 2015)  \
Test Accuracy            0.563917              0.429372             -0.247138

               RF (complex 2015)
Test Accuracy           0.506116

[1 rows x 24 columns]
```