1_density_calculation

April 24, 2023

1 SWB211 Project

Prepared by SWB Team: Tyler Will, Stefanie Senger, Fracisco Avalos Jr., Won Fy Lee

1.1 Executive Summary

-

  ### 1.1.1 Identify eligible candidates to the Kansas City Scholars (KCS) program in the Kansas City metropolitan area.

-

  ### 1.1.2 The U.S. census and survey data used was found as close as possible to match the eligibility requirements of KCS applicants.

-

  ### 1.1.3 Considerations on the findings given the approach is to be discussed:

  -

    ### 1.1.4 Block-level Map of following features

    *
    *
    *

1.1.5 Introduction

The goal of this project is to estimate the spatial distribution of Great Jobs KC eligible population using as fine-grained data as possible.

An individual is eligible for Great Jobs KC if:

1. 18 years or older
2. Live in one of the six eligible counties (KS: Wyandotte, Johnson; Missouri: Cass, Clay, Jackson, Platte)
3. Low or modest income evidenced by current earnings of less than $45,000 annually
4. Has not previously earned a bachelor's degree
5. Has not previously been awarded a KC Scholarship (Traditional or Adult Learner)
6. Not a current KC Scholars college scholarship awardee.
7. Lawfully present in the United States or DACA eligible and DACA applied/approved.

1.1.6 Data

The lowest-level geography data available from Census is block-level. A census block in KC have an average population of 21. In terms of relative size, a census tract contains 70 blocks and a census block-group contains an average of 23 blocks. Despite the small size of the block, only total population count information is available at the block-level.

The lowest-level geography data available for #1, #3 and #4 is block-group from 2021 American Community Survey. In addition, only marginal information of %age, %income and %education is available, while the information we need to define eligible population is joint density of %age$\%income\%$education.

1.1.7 Method

In order to derive the joint density, we assume variable independence (Assumption 1):

$$P(I, E, A|bg) = P(I|bg)P(E|bg)Pr(A|bg) \tag{1}$$

(1)

In order to leverage both block and block-group level data available, we consolidate the data from two different levels of geography by assuming that populations in blocks within a same block-group share same %age, %income and %education defined at the block-group, while respecting the total population counts defined at the block-level (Assumption 2):

$$N(I, E, A|b, bg) = P(I, E, A|bg) * N(b|bg) \tag{2}$$

(2)

Adjustment to Assumption 1: We found high correlation between %income and % education (~= 0.9). To adjust high correlation between % low income and % education lt BA, we run a simple bivariate linear regression with independent variable (X) defined as % annual income less than 45,000 dollars and dependent variable (Y) set as % population with less than bachelors degree. We use % education instead of %income as dependent variable, simply because the % low education is much higher than the % income less than 45k (63% vs 54%). The predicted value out of this regression gives us an adjusted share for Pr(I|bg) that account for the correlation between the two variable and it is strictly larger than the original Pr(I|bg).

$$\underbrace{\hat{Y}}_{\%education} = \underbrace{\alpha}_{intercept} + \underbrace{\beta}_{slope} * \underbrace{X}_{\%income} + \underbrace{\epsilon}_{error} \tag{3}$$

(3)

See Sections 9 - 13.

1.1.8 Preliminary Results

- We find that there are 611,675 eligible population in the Kansas city 6 counties. The eligible population make up 31 percent of total population in the 6 counties (=611,675/1,964,222).
- The three maps presented below show spatial information about the eligible population:
  1. N of eligible population (Block-level)
  2. N of eligible popluation per sq mile (Block-level)
  3. Hot spots of eligible population
- Block-level outcome data
- List of zipcode with rank ordered by the density of eligible population

[53]:
```
%%html
<iframe src="https://swb211.netlify.app/target_v2" width="1200" height="1000"></
↪iframe>
```

```
<IPython.core.display.HTML object>
```

[1]:
```
%%html
<iframe src="https://swb211.netlify.app/target_v3" width="1200" height="1000"></
↪iframe>
```

```
<IPython.core.display.HTML object>
```

[47]:
```
%%html
<iframe src="https://swb211.netlify.app/target_v4" width="1200" height="1000"></
↪iframe>
```

```
<IPython.core.display.HTML object>
```

[51]:
```
%%html


   <table style="font-size:0.9em">
            <thead><tr>
            <th> </th>
            <th>N</th>
            <th>Mean</th>

        </tr></thead>
        <tbody><tr>
            <td>s_bg_age_gt18</td>
            <td>37700</td>
            <td>0.75</td>

        </tr>
        <tr>
            <td>s_pinc_lt_45k</td>
            <td>37700</td>
            <td>0.56</td>

        </tr>
        <tr>
            <td>s_bg_educ_lt_bachelors</td>
            <td>37700</td>
            <td>0.63</td>

        </tr>
        <tr>
            <td>s_joint_age_educ_inc</td>
            <td>37700</td>
            <td>0.33</td>

        </tr>

    </tbody>
    </table>
```

```
<IPython.core.display.HTML object>
```

[52]:
```
%%html
<table style="font-size:0.8em">
            <thead><tr>
            <th>County</th>
            <th>N CensusTract</th>
            <th>N BlockGroup</th>
```

```
        <th>N Block</th>
        <th>Blocks per BG</th>

    </tr></thead>
    <tbody><tr>
        <td>Cass</td>
        <td>24</td>
        <td>83</td>
        <td>3571</td>
        <td>43</td>

    </tr>
    <tr>
        <td>Clay</td>
        <td>55</td>
        <td>192</td>
        <td>5222</td>
        <td>27</td>

    </tr>
    <tr>
        <td>Jackson</td>
        <td>227</td>
        <td>640</td>
        <td>14842</td>
         <td>23</td>

    </tr>
    <tr>
        <td>Johnson</td>
        <td>154</td>
        <td>462</td>
        <td>8235</td>
        <td>18</td>

    </tr>
    <tr>
        <td>Platte</td>
        <td>26</td>
        <td>80</td>
        <td>2475</td>
        <td>31</td>

    </tr>
    <tr>
        <td>Wyandotte</td>
        <td>64</td>
```

```
            <td>165</td>
            <td>3355</td>
            <td>20</td>

        </tr>
        <tr>
            <td>Total</td>
            <td>550</td>
            <td>1622</td>
           <td>37700</td>
            <td>23</td>

        </tr>
    </tbody>
</table>
```

```
<IPython.core.display.HTML object>
```

1.2 code begins here——————————————————————-

1.3 Joint Density Calculation

1.3.1 Data downloaded from https://www.nhgis.org/

- 2020 Census, Block level
  - Total Population Counts
- 2021 American Community Survey: 5-Year Data, Block-group level
  - Counts by age
  - Counts by education
  - Counts by earnings

1.3.2 1. Imports

[21]:
```
import pandas as pd
import os
```

1.3.3 Path Management

using `os.path.join`, to fit the paths for Linux/MacOS and Windows syntax, which is more robust: * Linux/MacOS syntax (e.g. `../folder_name`) * and Windows syntax (e.g. `..\\folder_name`)

[22]:
```
wd='/Users/wonfylee/Library/CloudStorage/GoogleDrive-leex5089@umn.edu/My Drive/
↪0.SWB/SWB211'

csv_path_population_block = os.path.join(wd, 'census_data', 'nhgis0202_csv',␣
↪'nhgis0202_ds248_2020_block.csv')
```

```
csv_path_education_income = os.path.join(wd, 'census_data', 'nhgis0197_csv',␣
↪'nhgis0197_ds254_20215_blck_grp.csv')
csv_path_personal_income = os.path.join(wd, 'census_data', 'nhgis0205_csv',␣
↪'nhgis0205_ds254_20215_blck_grp.csv')

csv_path_age = os.path.join(wd, 'census_data', 'nhgis0203_csv',␣
↪'nhgis0203_ds254_20215_blck_grp.csv')

dta_path_6_counties = os.path.join(wd, 'intermediate_data', 'b_KC_6counties.
↪dta')
dta_path_county_crosswalk = os.path.join(wd, 'intermediate_data',␣
↪'b_bg_county_crosswalk.dta')
```

1.3.4 2. DataFrame of population count per house block

Download block-level Data

Download codebook

[23]:
```
block_raw = pd.read_csv(csv_path_population_block, low_memory=False)
block_raw.columns = block_raw.columns.str.lower()

block_data = block_raw[['gisjoin', 'state','county','u7b001']]
block_data = block_data.rename(columns={'gisjoin': 'b_gisjoin'})
block_data = block_data.rename(columns={'u7b001': 'b_population'}) #␣
↪b_target_pop: Block level estimate of total population.

block_data
block_data['b_population'].mean()
```

[23]: 21.33652070461633

1.3.5 3. DataFrame of household income and individual's educational status accumulated per block group

A block group is a collection of several house blocks; approximatly 30-50 blocks form a block group. #### Download block group-level Data #### Download codebook

Note: We use personal earnings data instead of household income in the analysis.

[24]:
```
blockgroup_raw = pd.read_csv(csv_path_education_income)
blockgroup_raw.columns = blockgroup_raw.columns.str.lower()
col_list=blockgroup_raw[['aop8e002', 'aop8e003', 'aop8e004', 'aop8e005',␣
↪'aop8e006', 'aop8e007', 'aop8e008' ,'aop8e009', 'aop8e010', 'aop8e011',␣
↪'aop8e012', 'aop8e013', 'aop8e014', 'aop8e015', 'aop8e016', 'aop8e017',␣
↪'aop8e018', 'aop8e019', 'aop8e020', 'aop8e021']]
blockgroup_raw['bg_educ_lt_bachelors']=col_list.sum(axis=1) # summing␣
↪population count below bachelor's degree
```

```
col_list=blockgroup_raw[['aoqhe002', 'aoqhe003', 'aoqhe004', 'aoqhe005',␣
↪'aoqhe006', 'aoqhe007', 'aoqhe008', 'aoqhe009']]
blockgroup_raw['bg_inc_lt_45000']=col_list.sum(axis=1) # summing housdhold␣
↪inclome below 45 k

blockgroup_raw['s_bg_educ_lt_bachelors']=blockgroup_raw['bg_educ_lt_bachelors']/
↪blockgroup_raw['aop8e001'] # percentage of non-BA's over whole population␣
↪(creates Nan values where the population per block group is 0)
blockgroup_raw['s_bg_inc_lt_45000']=blockgroup_raw['bg_inc_lt_45000']/
↪blockgroup_raw['aoqhe001'] # percentage of low earning households over all␣
↪housholds (creates Nan values where the population per block group is 0)
blockgroup_raw = blockgroup_raw.rename(columns={'gisjoin': 'bg_gisjoin'})
bg_educ_inc=blockgroup_raw[['bg_gisjoin',␣
↪'bg_educ_lt_bachelors','bg_inc_lt_45000','s_bg_educ_lt_bachelors','s_bg_inc_lt_45000']]

bg_educ_inc
```

[24]:

```
            bg_gisjoin  bg_educ_lt_bachelors  bg_inc_lt_45000  \
0     G20000109526001                  1146              195
1     G20000109527001                   548              210
2     G20000109527002                   527              110
3     G20000109528001                   521              240
4     G20000109528002                   650              252
…                 …                     …                …
7487  G29051001277001                   661              211
7488  G29051001277002                   654              289
7489  G29051001277003                   176               79
7490  G29051001278001                   959              982
7491  G29051001278002                   290              363

      s_bg_educ_lt_bachelors  s_bg_inc_lt_45000
0                   0.861007           0.281792
1                   0.734584           0.466667
2                   0.780741           0.303867
3                   0.785822           0.551724
4                   0.672878           0.464945
…                        …                  …
7487                0.937589           0.703333
7488                1.000000           0.865269
7489                0.752137           0.576642
7490                0.762928           0.891916
7491                0.629067           0.782328

[7492 rows x 5 columns]
```

1.3.6 4. DataFrame of population's age accumulated per block group

Download block group-level Data

Download codebook A block group is a collection of several house blocks; approximatly 30-50 blocks form a block group.

[25]:
```
blockgroup_raw = pd.read_csv(csv_path_age)
blockgroup_raw.columns = blockgroup_raw.columns.str.lower()
blockgroup_raw.describe()
print(blockgroup_raw.info())
blockgroup_raw.dtypes
col_list=blockgroup_raw[['aonte007', 'aonte008', 'aonte009', 'aonte010',␣
 ↪'aonte011', 'aonte012', 'aonte013', 'aonte014', 'aonte015', 'aonte016'␣
 ↪,'aonte017', 'aonte018', 'aonte019' ,'aonte020', 'aonte021', 'aonte022',␣
 ↪'aonte023' ,'aonte024' ,'aonte025' ,'aonte031' ,'aonte032', 'aonte033',␣
 ↪'aonte034' ,'aonte035', 'aonte036', 'aonte037', 'aonte038', 'aonte039',␣
 ↪'aonte040', 'aonte041', 'aonte042', 'aonte043', 'aonte044', 'aonte045',␣
 ↪'aonte046', 'aonte047', 'aonte048', 'aonte049']]
blockgroup_raw['bg_age_gt18']=col_list.sum(axis=1) # summing population count␣
 ↪18 years and older
blockgroup_raw['s_bg_age_gt18']=blockgroup_raw['bg_age_gt18']/
 ↪blockgroup_raw['aonte001'] # percentage of population 18 years and older␣
 ↪over whole population (creates Nan values where the population per block␣
 ↪group is 0)
blockgroup_raw = blockgroup_raw.rename(columns={'gisjoin': 'bg_gisjoin'})
bg_age=blockgroup_raw[['bg_gisjoin', 'bg_age_gt18','s_bg_age_gt18']]

bg_age
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7492 entries, 0 to 7491
Columns: 1001 entries, gisjoin to aoslm036
dtypes: float64(76), int64(917), object(8)
memory usage: 57.2+ MB
None
```

[25]:

	bg_gisjoin	bg_age_gt18	s_bg_age_gt18
0	G20000109526001	1415	0.769859
1	G20000109527001	845	0.795669
2	G20000109527002	726	0.823129
3	G20000109528001	841	0.819688
4	G20000109528002	1221	0.822222
…	…	…	…
7487	G29051001277001	747	0.772492
7488	G29051001277002	784	1.000000
7489	G29051001277003	318	0.736111
7490	G29051001278001	1598	0.820329

```
7491  G29051001278002        1532      1.000000

[7492 rows x 3 columns]
```

1.3.7 5. DataFrame of population's personal income (earnings) per block group

Download block group-level Data

Download codebook Table: B20001. Sex by Earnings in the Past 12 Months (in 2021 Inflation-Adjusted Dollars) for the Population 16 Years and Over with Earnings in the Past 12 Months

Universe: Population 16 years and over with earnings

Earnings As noted above, in Census Bureau terminology, earnings are a subset of income. Specifically, earnings are wages or salary from a job, or income from being self-employed. Other kinds of income, not included in earnings, include social security payments, interest and dividends, income from property rental, pensions, public assistance, and child support.

[26]:
```
blockgroup_raw = pd.read_csv(csv_path_personal_income)
blockgroup_raw.columns = blockgroup_raw.columns.str.lower()
blockgroup_raw.describe()
print(blockgroup_raw.info())
blockgroup_raw.dtypes
col_list=blockgroup_raw[['aor6e003', 'aor6e004', 'aor6e005', 'aor6e006',␣
 ↪'aor6e007', 'aor6e008', 'aor6e009', 'aor6e010', 'aor6e011', 'aor6e012',␣
 ↪'aor6e013', 'aor6e014', 'aor6e015', 'aor6e016', 'aor6e024' ,'aor6e025',␣
 ↪'aor6e026', 'aor6e027', 'aor6e028', 'aor6e029', 'aor6e030', 'aor6e031',␣
 ↪'aor6e032', 'aor6e033', 'aor6e034', 'aor6e035', 'aor6e036', 'aor6e037']]
blockgroup_raw['bg_pinc_lt_45k']=col_list.sum(axis=1) # summing population␣
 ↪count 18 years and older
blockgroup_raw['s_bg_pinc_lt_45k']=blockgroup_raw['bg_pinc_lt_45k']/
 ↪blockgroup_raw['aor6e001'] # percentage of population 18 years and older␣
 ↪over whole population (creates Nan values where the population per block␣
 ↪group is 0)
blockgroup_raw = blockgroup_raw.rename(columns={'gisjoin': 'bg_gisjoin'})
bg_personal_income=blockgroup_raw[['bg_gisjoin',␣
 ↪'bg_pinc_lt_45k','s_bg_pinc_lt_45k']]

bg_personal_income
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7492 entries, 0 to 7491
Columns: 129 entries, gisjoin to aor6m043
dtypes: float64(30), int64(91), object(8)
memory usage: 7.4+ MB
None
```

[26]:
```
             bg_gisjoin  bg_pinc_lt_45k  s_bg_pinc_lt_45k
0     G20000109526001             523          0.561159
1     G20000109527001             444          0.805808
2     G20000109527002             324          0.642857
3     G20000109528001             434          0.811215
4     G20000109528002             539          0.707349
…                 …              …                 …
7487  G29051001277001             232          0.760656
7488  G29051001277002             251          0.886926
7489  G29051001277003             165          0.868421
7490  G29051001278001             734          0.890777
7491  G29051001278002             945          0.918367

[7492 rows x 3 columns]
```

1.3.8 6. prepare cross-walk data

[27]:
```
##b_KC_6counties
b_KC_6counties = pd.read_stata(dta_path_6_counties)
b_KC_6counties.columns = b_KC_6counties.columns.str.lower()

##JOIN
b_bg_county_crosswalk = pd.read_stata(dta_path_county_crosswalk)
b_bg_county_crosswalk.columns = b_bg_county_crosswalk.columns.str.lower()
b_bg_county_crosswalk = b_bg_county_crosswalk[['b_gisjoin', 'bg_gisjoin']] #␣
↪cutting down on unnecessary columns

b_KC_6counties
b_bg_county_crosswalk
```

[27]:
```
                b_gisjoin       bg_gisjoin
0      G20009100500001000  G20009100500001
1      G20009100500001001  G20009100500001
2      G20009100500001002  G20009100500001
3      G20009100500001003  G20009100500001
4      G20009100500001004  G20009100500001
…                     …              …
37696  G29016509800001121  G29016509800001
37697  G29016509800001122  G29016509800001
37698  G29016509800001123  G29016509800001
37699  G29016509800001124  G29016509800001
37700  G29016509800001125  G29016509800001

[37701 rows x 2 columns]
```

1.3.9 7. Merge block and block-group data

[28]:
```
#merge B and BG level data, calculate target_density
merge1=pd.merge(block_data, b_KC_6counties,on=['b_gisjoin' ])  # merge to␣
↪restrict area to 6 counties in KC (426161 to 37701)
merge2=pd.merge(merge1, b_bg_county_crosswalk,on=['b_gisjoin' ])  # block␣
↪block-group county crosswalk file
merge3=pd.merge(merge2, bg_age,on=['bg_gisjoin' ])  # add bg-level age
merge4=pd.merge(merge3, bg_educ_inc,on=['bg_gisjoin' ])  # add bg-level␣
↪bg_educ_inc
merge5=pd.merge(merge4, bg_personal_income,on=['bg_gisjoin' ])  # add bg-level␣
↪bg_educ_inc




# merge4.isna().sum().sort_values(ascending=False) # checking for Nan values
merge5 = merge5.fillna(0) # replacing Nan values with 0
                          # (admissible, because those came into being by␣
↪devision by 0 where the population count per block group was 0)
                          # (the percentage of target populaton in block groups␣
↪without any population should be 0, presupposedly the data is correct)




merge5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 37701 entries, 0 to 37700
Data columns (total 15 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   b_gisjoin               37701 non-null  object
 1   state                   37701 non-null  object
 2   county                  37701 non-null  object
 3   b_population            37701 non-null  int64
 4   fid                     37701 non-null  int32
 5   shape_area              37701 non-null  float32
 6   bg_gisjoin              37701 non-null  object
 7   bg_age_gt18             37701 non-null  int64
 8   s_bg_age_gt18           37701 non-null  float64
 9   bg_educ_lt_bachelors    37701 non-null  int64
 10  bg_inc_lt_45000         37701 non-null  int64
 11  s_bg_educ_lt_bachelors  37701 non-null  float64
 12  s_bg_inc_lt_45000       37701 non-null  float64
 13  bg_pinc_lt_45k          37701 non-null  int64
 14  s_bg_pinc_lt_45k        37701 non-null  float64
dtypes: float32(1), float64(4), int32(1), int64(5), object(4)
```

memory usage: 4.3+ MB

1.3.10 8. Calculate joint density of target population

In this case, we assume indepencence between the variables income, age and educational status, thus getting the joint probability P(I,E,A|bg)=P(I|bg)P(E|bg)Pr(A|bg).

Response to Stefanie: for "target_pop_per_sq_mile" just wanted to change from per sq meter to per sq mile, so just needed a bracket in the denominator (merge5['shape_area'] / whole_area_6_counties)!

[29]:
```
whole_population_6_counties=merge5['b_population'].sum()
whole_area_6_counties = 2589973.632302

# joint probability age*educ*income of target population
merge5['s_joint_age_educ_inc']=merge5['s_bg_age_gt18']*merge5['s_bg_educ_lt_bachelors']*merge5

# block-level estimate of target population
merge5['b_target_pop']=merge5['b_population']*merge5['s_joint_age_educ_inc']

# calculating density and distribution per sq miles
merge5['target_density']=(merge5['b_target_pop'] / whole_population_6_counties).
 ↪fillna(0)
merge5['target_pop_per_sq_mile']=merge5['b_target_pop'] / (merge5['shape_area']␣
 ↪/ whole_area_6_counties)
```

Working comment: Assuming independence of our variables (income, age and educational status) plus the very strict definition of household income instead of individual income makes us miss most of the target population.

Response: To address the concern about high correlation between income and educational status. I propose following adjustment to the density calculation.

1.3.11 9. check correlation between income and education

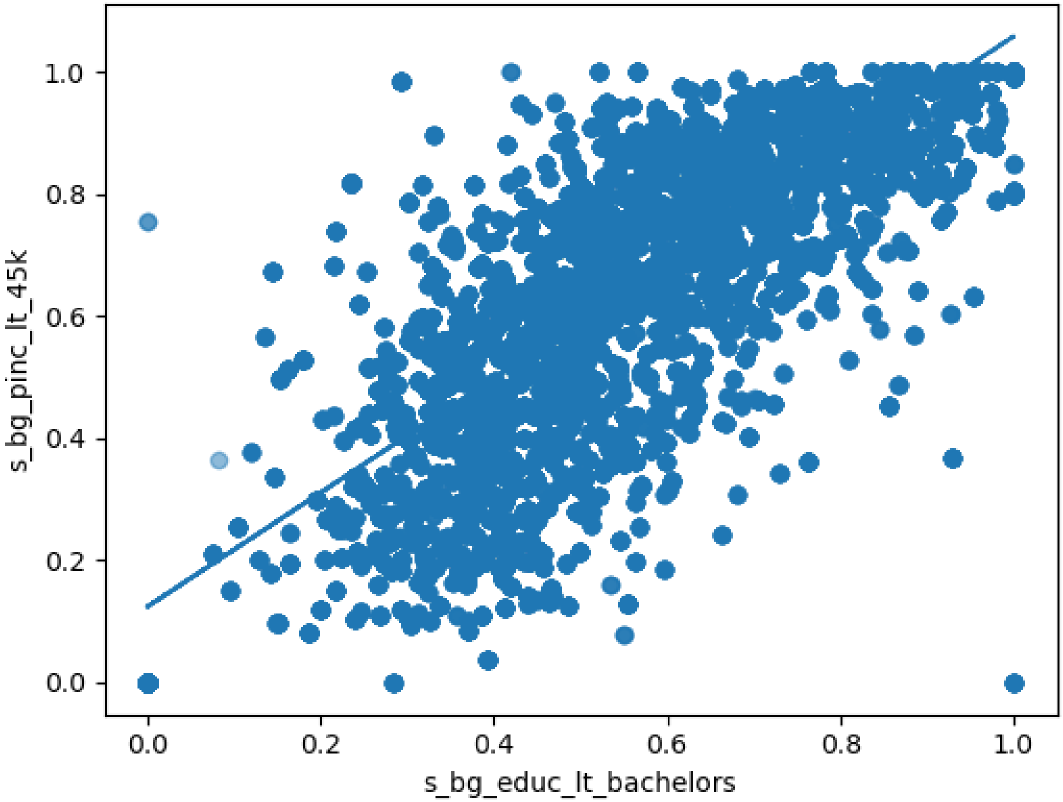
[32]:
```
import matplotlib.pyplot as plt
import numpy as np

plt.scatter(merge5['s_bg_pinc_lt_45k'], merge5['s_bg_educ_lt_bachelors'], ␣
 ↪alpha=0.5)

#obtain m (slope) and b(intercept) of linear regression line
m, b = np.polyfit(merge5['s_bg_pinc_lt_45k'], ␣
 ↪merge5['s_bg_educ_lt_bachelors'], 1)

#add linear regression line to scatterplot
x_pinc_lt_45k=merge5['s_bg_pinc_lt_45k']
plt.plot(merge5['s_bg_pinc_lt_45k'], m*x_pinc_lt_45k+b)
```

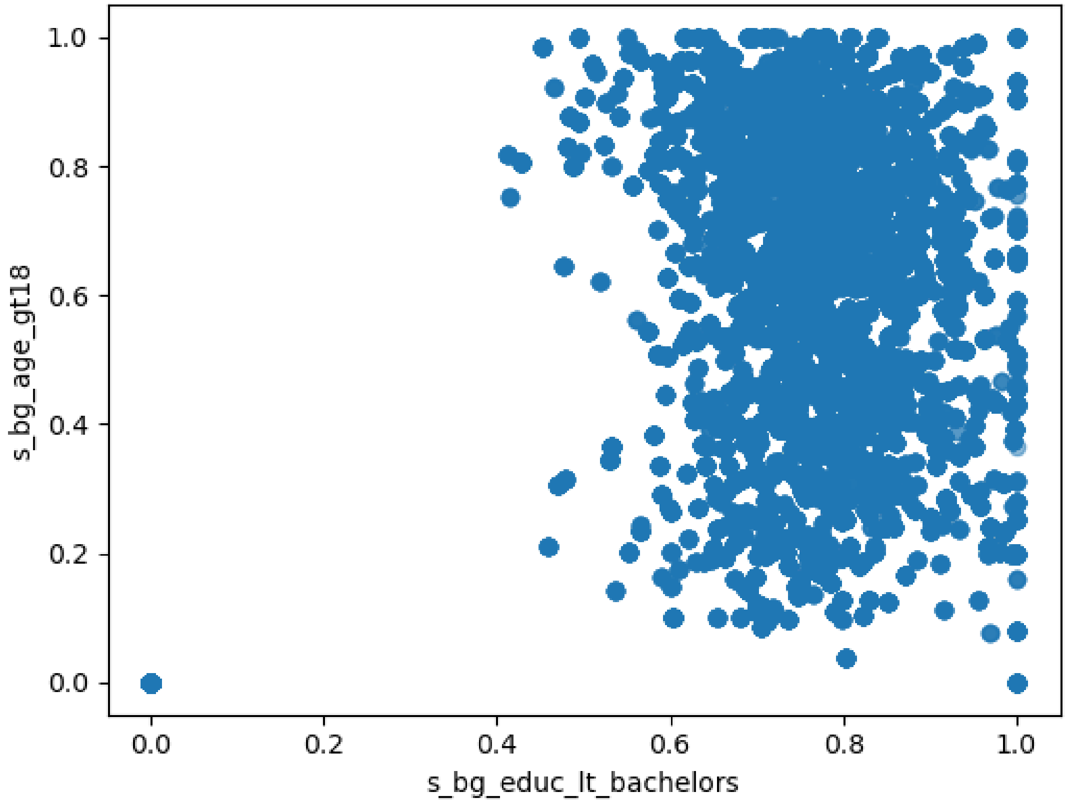
```
plt.xlabel("s_bg_educ_lt_bachelors")
plt.ylabel("s_bg_pinc_lt_45k")
plt.show()
```



1.3.12 10. check correlation between income and age

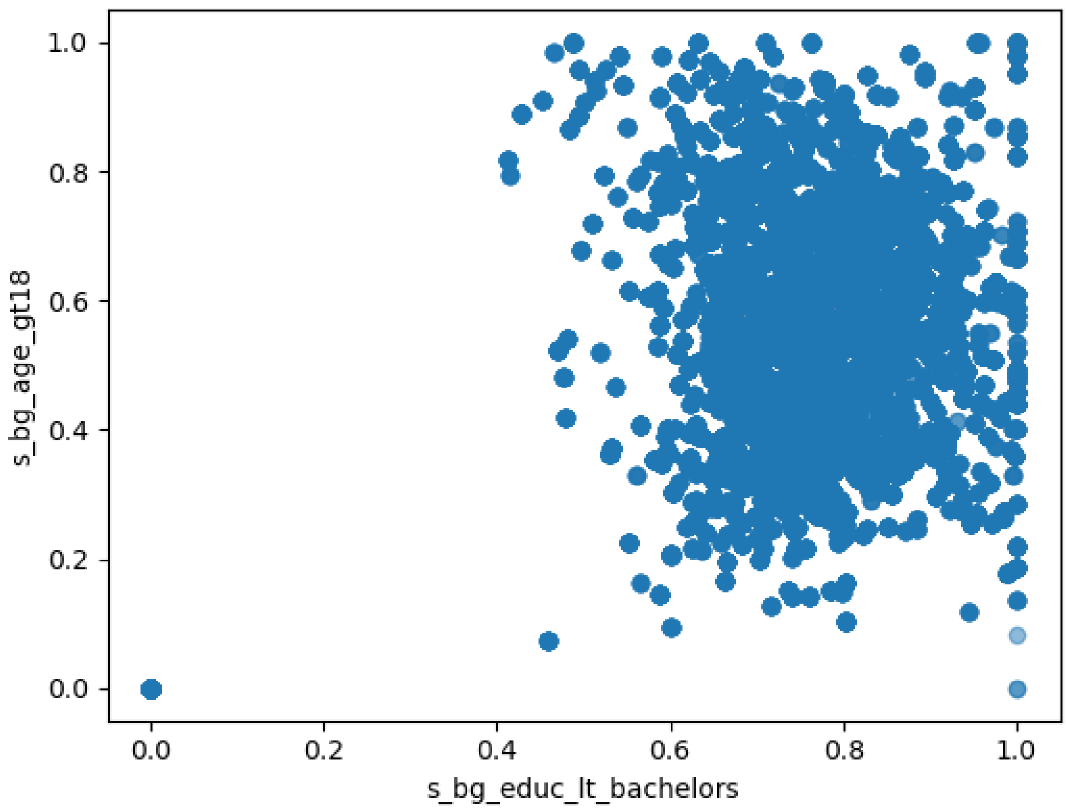
[33]:
```
plt.scatter(merge5['s_bg_age_gt18'], merge5['s_bg_educ_lt_bachelors'],  alpha=0.
↪5)
plt.xlabel("s_bg_educ_lt_bachelors")
plt.ylabel("s_bg_age_gt18")
plt.show()

#age correlation is low with other two vars.
```



[34]:
```
plt.scatter(merge5['s_bg_age_gt18'], merge5['s_bg_pinc_lt_45k'],  alpha=0.5)
plt.xlabel("s_bg_educ_lt_bachelors")
plt.ylabel("s_bg_age_gt18")
plt.show()

#age correlation is low with other two vars.
```



1.3.13 11. Adjustment to the high correlation between educ and income based on eq (3)

[35]:
```
from sklearn.linear_model import LinearRegression


merge5 = merge5.dropna(axis=0)
# Create a numpy array of data:
x = np.array(merge5['s_bg_pinc_lt_45k']).reshape((-1, 1))
y = np.array(merge5['s_bg_educ_lt_bachelors'])
#run bivariate linear regression
regr =  LinearRegression()
results=regr.fit(x,y)

# Make adjustment index (predicted y) based on equation (1)
merge5['y_pred'] = regr.predict(x).reshape((-1, 1))

print("Coefficients: \n", regr.coef_) # coefficient of 0.93 suggest high␣
 ↪correlation between the two variables.
print("predicted y: \n", merge5['y_pred'].mean())
print("y: \n", y.mean())
```

```python
print("x: \n", x.mean())
```

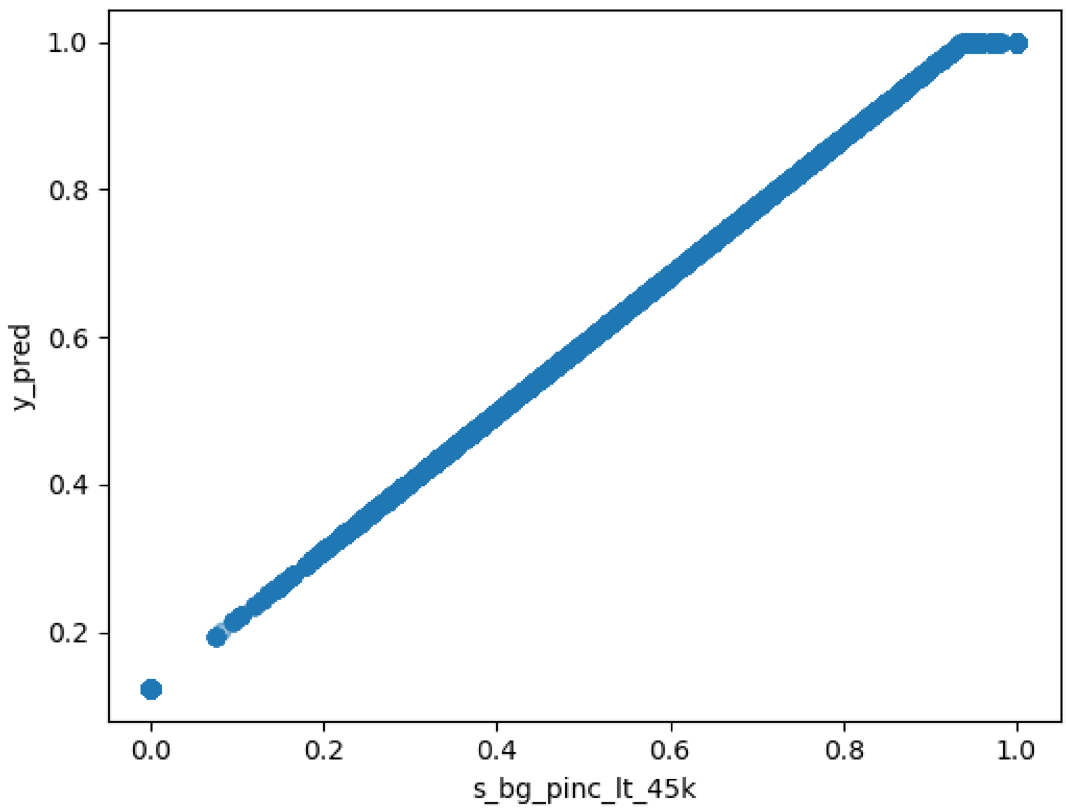
```
Coefficients:
 [0.93413271]
predicted y:
 0.6324534969310122
y:
 0.632453496931012
x:
 0.5446789080033402
```

replace predicted value to 1 if y_pred>1, because a fraction can't go over 1.

[36]:
```python
merge5.loc[merge5.y_pred > 1, 'y_pred'] = 1
```

As shown in the graph below, it is basically addition of intercept and slope*%income to the original %income data. The mean of y_pred is 0.63, while the original mean of %income is 0.54. I propose to use y_pred instead of s_bg_pinc_lt_45k in calculating the joint density.

[37]:
```python
plt.scatter(merge5['s_bg_pinc_lt_45k'], merge5['y_pred'],  alpha=0.5)
plt.xlabel("s_bg_pinc_lt_45k")
plt.ylabel("y_pred")
plt.show()
print("s_bg_pinc_lt_45k: \n", merge5['s_bg_pinc_lt_45k'].mean())
print("y_pred: \n", merge5['y_pred'].mean())
```




```
s_bg_pinc_lt_45k:
 0.5446789080033402
y_pred:
 0.6318152678099239
```

1.3.14 12. Revision of joint density, call it s__joint__age__educ__inc__adj

[38]:
```
# joint probability age*educ*income of target population (using y_pred)
merge5['s_joint_age_educ_inc_adj']=merge5['s_bg_age_gt18']*merge5['s_bg_educ_lt_bachelors']*me

# block-level estimate of target population
merge5['b_target_pop_adj']=merge5['b_population']*merge5['s_joint_age_educ_inc_adj']

# calculating density and distribution per sq miles
merge5['target_density_adj']=(merge5['b_target_pop_adj'] /␣
↪whole_population_6_counties).fillna(0)
merge5['target_pop_per_sq_mile_adj']=merge5['b_target_pop_adj'] /␣
↪(merge5['shape_area'] / whole_area_6_counties)
```

1.3.15 13. After the adjustment for correlation between income and education, joint density changes from 0.29 to 0.33

[39]:

```python
print("s_joint_age_educ_inc: \n", merge5['s_joint_age_educ_inc'].mean())
print("s_joint_age_educ_inc_adj: \n", merge5['s_joint_age_educ_inc_adj'].mean())
merge5.info()
```

```
s_joint_age_educ_inc:
 0.29059760078943736
s_joint_age_educ_inc_adj:
 0.3308518894458803
<class 'pandas.core.frame.DataFrame'>
Int64Index: 37701 entries, 0 to 37700
Data columns (total 24 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   b_gisjoin                   37701 non-null  object
 1   state                       37701 non-null  object
 2   county                      37701 non-null  object
 3   b_population                37701 non-null  int64
 4   fid                         37701 non-null  int32
 5   shape_area                  37701 non-null  float32
 6   bg_gisjoin                  37701 non-null  object
 7   bg_age_gt18                 37701 non-null  int64
 8   s_bg_age_gt18               37701 non-null  float64
 9   bg_educ_lt_bachelors        37701 non-null  int64
 10  bg_inc_lt_45000             37701 non-null  int64
 11  s_bg_educ_lt_bachelors      37701 non-null  float64
 12  s_bg_inc_lt_45000           37701 non-null  float64
 13  bg_pinc_lt_45k              37701 non-null  int64
 14  s_bg_pinc_lt_45k            37701 non-null  float64
 15  s_joint_age_educ_inc        37701 non-null  float64
 16  b_target_pop                37701 non-null  float64
 17  target_density              37701 non-null  float64
 18  target_pop_per_sq_mile      37701 non-null  float64
 19  y_pred                      37701 non-null  float64
 20  s_joint_age_educ_inc_adj    37701 non-null  float64
 21  b_target_pop_adj            37701 non-null  float64
 22  target_density_adj          37701 non-null  float64
 23  target_pop_per_sq_mile_adj  37701 non-null  float64
dtypes: float32(1), float64(13), int32(1), int64(5), object(4)
memory usage: 6.9+ MB
```

[40]:

```
final_block_data=merge5[['fid', 'county' ,'bg_gisjoin' ,'b_gisjoin'␣
 ↪,'b_population', 'bg_age_gt18', 'bg_educ_lt_bachelors',␣
 ↪'bg_inc_lt_45000','s_bg_age_gt18', 's_bg_educ_lt_bachelors',␣
 ↪'s_bg_inc_lt_45000', 's_joint_age_educ_inc' ,'b_target_pop',␣
 ↪'target_pop_per_sq_mile', 'target_density', 's_joint_age_educ_inc_adj'␣
 ↪,'b_target_pop_adj', 'target_pop_per_sq_mile_adj', 'target_density_adj']]
final_block_data
```

[40]:

```
         fid          county        bg_gisjoin           b_gisjoin  \
0          0  Johnson County  G20009100500001  G20009100500001000
1          1  Johnson County  G20009100500001  G20009100500001001
2          2  Johnson County  G20009100500001  G20009100500001002
3          3  Johnson County  G20009100500001  G20009100500001003
4          4  Johnson County  G20009100500001  G20009100500001004
…        …             …               …                  …
37696  37696   Platte County  G29016509800001  G29016509800001121
37697  37697   Platte County  G29016509800001  G29016509800001122
37698  37698   Platte County  G29016509800001  G29016509800001123
37699  37699   Platte County  G29016509800001  G29016509800001124
37700  37700   Platte County  G29016509800001  G29016509800001125

       b_population  bg_age_gt18  bg_educ_lt_bachelors  bg_inc_lt_45000  \
0                52          480                   237              130
1                47          480                   237              130
2                51          480                   237              130
3                58          480                   237              130
4               138          480                   237              130
…               …          …                     …                …
37696             0            0                     0                0
37697             0            0                     0                0
37698             0            0                     0                0
37699             0            0                     0                0
37700             0            0                     0                0

       s_bg_age_gt18  s_bg_educ_lt_bachelors  s_bg_inc_lt_45000  \
0           0.914286                0.697059           0.546218
1           0.914286                0.697059           0.546218
2           0.914286                0.697059           0.546218
3           0.914286                0.697059           0.546218
4           0.914286                0.697059           0.546218
…              …                      …                  …
37696       0.000000                0.000000           0.000000
37697       0.000000                0.000000           0.000000
37698       0.000000                0.000000           0.000000
37699       0.000000                0.000000           0.000000
37700       0.000000                0.000000           0.000000
```

```
       s_joint_age_educ_inc  b_target_pop  target_pop_per_sq_mile  \
0                  0.498382     25.915841             2412.201467
1                  0.498382     23.423933             2254.971812
2                  0.498382     25.417459             2494.954108
3                  0.498382     28.906130             2765.100132
4                  0.498382     68.776654             2391.340569
…                       …            …                      …
37696              0.000000      0.000000                0.000000
37697              0.000000      0.000000                0.000000
37698              0.000000      0.000000                0.000000
37699              0.000000      0.000000                0.000000
37700              0.000000      0.000000                0.000000

       target_density  s_joint_age_educ_inc_adj  b_target_pop_adj  \
0            0.000013                  0.544359         28.306653
1            0.000012                  0.544359         25.584860
2            0.000013                  0.544359         27.762294
3            0.000015                  0.544359         31.572805
4            0.000035                  0.544359         75.121503
…                 …                        …                 …
37696        0.000000                  0.000000          0.000000
37697        0.000000                  0.000000          0.000000
37698        0.000000                  0.000000          0.000000
37699        0.000000                  0.000000          0.000000
37700        0.000000                  0.000000          0.000000

       target_pop_per_sq_mile_adj  target_density_adj
0                     2634.734136            0.000014
1                     2462.999584            0.000013
2                     2725.120951            0.000014
3                     3020.188740            0.000016
4                     2611.948759            0.000038
…                             …                  …
37696                    0.000000            0.000000
37697                    0.000000            0.000000
37698                    0.000000            0.000000
37699                    0.000000            0.000000
37700                    0.000000            0.000000

[37701 rows x 19 columns]
```

1.3.16 14. save final output file

[175]:

```
final_block_data.to_excel("G:\\My Drive\\0.SWB\\SWB211/intermediate_data/
↪block_level_target_population_outofpython_20230414.xlsx",index=False)
final_block_data.to_csv("G:\\My Drive\\0.SWB\\SWB211/intermediate_data/
↪block_level_target_population_outofpython_20230414.csv",index=False)
```