Midterm 2_8

February 8, 2021

0.1 Midterm Project: Tracking Water Bill Debt across California

0.1.1 Load Libraries and Data

The first type of data I'm working with is a combination of 2 datasets (which has previously been merged by zip code) * Water bill debt information * American Community Survey Data

These two datasets, together, will help me better understand where drinking water debt is distributed across the state as well as which demographic factors coincide with higher or lower debt levels.

The second piece of my data is the spatial component. It is a GeoJson file of all zip code boundaries in the state of California.

First, I am going to load my libraries. I want to be able to read and map my data, so I've selected the 5 following libraries.

[1]:
```
import pandas as pd
import geopandas as gpd
import contextily as ctx
import matplotlib.pyplot as plt
import urllib.request, json
import plotly.express as px
from ipywidgets import interact
```

Now that I can read my data with pandas, I am going to upload the water bill data and zip code boundary file.

[2]:
```
acs = pd.read_csv('Data/URBNPL206A Dataset - Sheet1.csv')

zip = gpd.read_file('Data/ca_california_zip_codes_geo.min.json')
```

0.1.2 Explore the Data

Now that my data are uploaded, I need to get a sense of how they look, if any data are missing, etc. For now, I am going to focus on my water bill debt/demographic data since it is in .csv. Later, I will merge it with the GeoJson file.

[3]:
```
acs.shape
```

[3]:
```
(1073, 52)
```

This dataset has 1067 entries and 52 columns - it's big!

I also want to get a sense of the data itsef: missing data, data type, etc.

[4]:
```
acs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1073 entries, 0 to 1072
Data columns (total 52 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   Zip Codes                                                 1073 non-null
object
 1   Count of Zip Code                                         1072 non-null
float64
 2   Sum of Less than $100                                     934 non-null
float64
 3   Sum of $100-$200                                          965 non-null
float64
 4   Sum of $200-$300                                          965 non-null
float64
 5   Sum of $300-$400                                          954 non-null
float64
 6   Sum of $400-$500                                          941 non-null
float64
 7   Sum of $500-$600                                          917 non-null
float64
 8   Sum of $600-$700                                          914 non-null
float64
 9   Sum of $700-$800                                          906 non-null
float64
 10  Sum of $800-$900                                          895 non-null
float64
 11  Sum of $900-$1000                                         894 non-null
float64
 12  Sum of More than $1000                                    936 non-null
float64
 13  Sum of Total number of delinquent residential accounts    1063 non-null
float64
 14  pop                                                       1030 non-null
float64
 15  nhw                                                       1030 non-null
float64
 16  black                                                     1030 non-null
float64
 17  hisp                                                      1030 non-null
```

```
float64
 18  asian                                                      1030 non-null
float64
 19  noncitizen                                                 1030 non-null
float64
 20  immigrants                                                 1030 non-null
float64
 21  ohu                                                        1030 non-null
float64
 22  lep_hh                                                     1030 non-null
float64
 23  dpov                                                       1030 non-null
float64
 24  npov                                                       1030 non-null
float64
 25  mhhi                                                       1030 non-null
float64
 26  overcrowded                                                1030 non-null
float64
 27  no_veh_hh                                                  1030 non-null
float64
 28  w_broadband                                                1030 non-null
float64
 29  pop_19_64                                                  1030 non-null
float64
 30  uninsured_19_64                                            1030 non-null
float64
 31  pct_nhw                                                    1030 non-null
float64
 32  pct_black                                                  1030 non-null
float64
 33  pct_hisp                                                   1030 non-null
float64
 34  pct_asian                                                  1030 non-null
float64
 35  pct_noncitizen                                             1030 non-null
float64
 36  pct_immigrants                                             1030 non-null
float64
 37  pct_lep_hh                                                 1030 non-null
object
 38  pct_povt                                                   1030 non-null
object
 39  pct_overcrowded                                            1030 non-null
object
 40  pct_no_veh_hh                                              1030 non-null
object
 41  pct_broadband                                              1030 non-null
```

```
object
 42  pct_no_broadband                                         1030 non-null
object
 43  pct_uninsured_19_64                                      1030 non-null
float64
 44  aggveh                                                   1030 non-null
float64
 45  pct_no_hins                                              1030 non-null
float64
 46  veh_person                                               1030 non-null
float64
 47  Total Population in Occupied Housing Units: Renter Occupied  1030 non-null
float64
 48  Owner Occupied Pop                                       1030 non-null
float64
 49  % Renter Pop                                             1030 non-null
float64
 50  % Owner Pop                                              1030 non-null
float64
 51  Households                                               1031 non-null
float64
dtypes: float64(45), object(7)
memory usage: 436.0+ KB
```

So here we can see that there are fewer datapoints here than total zip codes in California. There are over 1,700 zips in the state. This can largely be attributed to the fact that the water bill debt data was conducted via a survey distribted by the California State Water Resources Control Board. Survey responses have their limitations in that they are completed on a voluntary basis. It is worth keeping in mind as I continue with my analysis that this is not a complete dataset of all zip codes in the state. Hopefullly, this dataset is complete enough though to draw some conclusions about water bill debt trends and demographics.

[5]:
```
acs.head()
```

[5]:
```
  Zip Codes  Count of Zip Code  Sum of Less than $100  Sum of $100-$200  \
0     90001                3.0                 5726.0            4937.0
1     90002                3.0                 3130.0            2152.0
2     90003                2.0                 1829.0            1880.0
3     90004                1.0                 2199.0            1659.0
4     90005                1.0                 1712.0            1107.0

   Sum of $200-$300  Sum of $300-$400  Sum of $400-$500  Sum of $500-$600  \
0            1582.0             684.0             395.0             283.0
1            1052.0             708.0             493.0             385.0
2            1562.0            1169.0             941.0             782.0
3            1119.0             735.0             502.0             387.0
4             598.0             401.0             281.0             175.0
```

```
   Sum of $600-$700  Sum of $700-$800  …  pct_no_broadband  \
0             220.0             137.0  …      0.2991675715
1             343.0             281.0  …      0.3798992602
2             673.0             513.0  …      0.3209552169
3             279.0             223.0  …      0.2220199354
4             146.0              95.0  …      0.3019705632

   pct_uninsured_19_64   aggveh  pct_no_hins  veh_person  \
0             0.243428  24689.0     0.168425    0.418635
1             0.255720  21749.0     0.177007    0.409501
2             0.261466  28622.0     0.192422    0.393478
3             0.247983  29013.0     0.195940    0.471097
4             0.328389  16170.0     0.256415    0.409585

   Total Population in Occupied Housing Units: Renter Occupied  \
0                                            38172.0
1                                            33035.0
2                                            50340.0
3                                            49509.0
4                                            36035.0

   Owner Occupied Pop  % Renter Pop  % Owner Pop  Households
0             20803.0      0.647257     0.352743     14174.0
1             20076.0      0.621999     0.378001     13546.0
2             22401.0      0.692044     0.307956     18523.0
3             12077.0      0.803900     0.196100     25192.0
4              3444.0      0.912764     0.087236     18291.0

[5 rows x 52 columns]
```

I actually want to over-write this feature so I can see all 52 columns, pick those of interest, and then remove the others.

[6]:
```
pd.set_option('display.max_columns', None)
```

And now I'll check my work just to make sure….

[7]:
```
acs.head()
```

[7]:
```
  Zip Codes  Count of Zip Code  Sum of Less than $100  Sum of $100-$200  \
0     90001                3.0                 5726.0            4937.0
1     90002                3.0                 3130.0            2152.0
2     90003                2.0                 1829.0            1880.0
3     90004                1.0                 2199.0            1659.0
4     90005                1.0                 1712.0            1107.0

   Sum of $200-$300  Sum of $300-$400  Sum of $400-$500  Sum of $500-$600  \
0            1582.0             684.0             395.0             283.0
```

```
1           1052.0              708.0              493.0              385.0
2           1562.0             1169.0              941.0              782.0
3           1119.0              735.0              502.0              387.0
4            598.0              401.0              281.0              175.0

   Sum of $600-$700  Sum of $700-$800  Sum of $800-$900  Sum of $900-$1000  \
0             220.0             137.0             132.0               97.0
1             343.0             281.0             231.0              201.0
2             673.0             513.0             482.0              401.0
3             279.0             223.0             206.0              164.0
4             146.0              95.0              95.0               58.0

   Sum of More than $1000  \
0                   709.0
1                  1779.0
2                  3437.0
3                  1116.0
4                   426.0

   Sum of Total number of delinquent residential accounts      pop      nhw  \
0                                            14902.0       58975.0    413.0
1                                            10755.0       53111.0    223.0
2                                            13669.0       72741.0    392.0
3                                             8589.0       61586.0  10820.0
4                                             5094.0       39479.0   3020.0

     black     hisp    asian  noncitizen  immigrants      ohu  lep_hh  \
0   5228.0  53086.0    129.0     17099.0     24040.0  13815.0  2876.0
1  10354.0  41673.0    322.0     13519.0     18628.0  12706.0  2203.0
2  16136.0  56050.0    257.0     19895.0     27310.0  17127.0  2829.0
3   2393.0  31479.0  15485.0     18353.0     30512.0  21971.0  5650.0
4   2423.0  19437.0  13849.0     15352.0     23346.0  16442.0  6799.0

      dpov     npov     mhhi  overcrowded  no_veh_hh  w_broadband  pop_19_64  \
0  58816.0  16911.0  38521.0       1902.0     1619.0       9682.0    37128.0
1  52845.0  17365.0  35410.0        832.0     1855.0       7879.0    32868.0
2  72362.0  22186.0  37226.0       1761.0     2830.0      11630.0    45876.0
3  61417.0  11092.0  48754.0       2825.0     3769.0      17093.0    44991.0
4  39331.0  11036.0  35149.0       3379.0     4940.0      11477.0    29054.0

   uninsured_19_64   pct_nhw  pct_black  pct_hisp  pct_asian  pct_noncitizen  \
0           9038.0  0.007003   0.088648  0.900144   0.002187        0.289936
1           8405.0  0.004199   0.194950  0.784640   0.006063        0.254542
2          11995.0  0.005389   0.221828  0.770542   0.003533        0.273505
3          11157.0  0.175689   0.038856  0.511139   0.251437        0.298006
4           9541.0  0.076496   0.061374  0.492338   0.350794        0.388865
```

```
   pct_immigrants    pct_lep_hh      pct_povt pct_overcrowded pct_no_veh_hh  \
0        0.407630   0.208179515   0.287523803    0.1376764387   0.1171914586
1        0.350737  0.1733826539  0.3286025168   0.06548087518   0.1459940186
2        0.375442  0.1651777895  0.3065973854    0.1028201086   0.1652361768
3        0.495437  0.2571571617  0.1806014621    0.1285785809   0.1715443084
4        0.591352   0.413514171  0.2805929165    0.2055102786   0.3004500669

  pct_broadband pct_no_broadband  pct_uninsured_19_64   aggveh  pct_no_hins  \
0  0.7008324285     0.2991675715             0.243428  24689.0     0.168425
1  0.6201007398     0.3798992602             0.255720  21749.0     0.177007
2  0.6790447831     0.3209552169             0.261466  28622.0     0.192422
3  0.7779800646     0.2220199354             0.247983  29013.0     0.195940
4  0.6980294368     0.3019705632             0.328389  16170.0     0.256415

   veh_person  Total Population in Occupied Housing Units: Renter Occupied  \
0    0.418635                                            38172.0
1    0.409501                                            33035.0
2    0.393478                                            50340.0
3    0.471097                                            49509.0
4    0.409585                                            36035.0

   Owner Occupied Pop  % Renter Pop  % Owner Pop  Households
0             20803.0      0.647257     0.352743     14174.0
1             20076.0      0.621999     0.378001     13546.0
2             22401.0      0.692044     0.307956     18523.0
3             12077.0      0.803900     0.196100     25192.0
4              3444.0      0.912764     0.087236     18291.0
```

Okay, so looking at this data, there are some columns of interest: I want to keep zip codes, as well as the scaled debt values from less than 100 to over 1,000, the total number of deliquent accounts, the population, median household income, percent black, percent hispanic, percent asian, percent poverty, percent renter, percent owner, and households.

This is much more expansive than my actual analysis will be, but I want some flexibliity in what I analyze in case some relationships I've hypothesized do not actually exist.

0.1.3 Cleaning the Data

Now that I have a sense of the columns I want to keep, I'm going to remove the rest, just so the data is a bit more manageable.

[8]:
```
list(acs)
```

[8]:
```
['Zip Codes',
 'Count of Zip Code',
 'Sum of Less than $100',
 'Sum of $100-$200',
 'Sum of $200-$300',
```

```
'Sum of $300-$400',
'Sum of $400-$500',
'Sum of $500-$600',
'Sum of $600-$700',
'Sum of $700-$800',
'Sum of $800-$900',
'Sum of $900-$1000',
'Sum of More than $1000',
'Sum of Total number of delinquent residential accounts',
'pop',
'nhw',
'black',
'hisp',
'asian',
'noncitizen',
'immigrants',
'ohu',
'lep_hh',
'dpov',
'npov',
'mhhi',
'overcrowded',
'no_veh_hh',
'w_broadband',
'pop_19_64',
'uninsured_19_64',
'pct_nhw',
'pct_black',
'pct_hisp',
'pct_asian',
'pct_noncitizen',
'pct_immigrants',
'pct_lep_hh',
'pct_povt',
'pct_overcrowded',
'pct_no_veh_hh',
'pct_broadband',
'pct_no_broadband',
'pct_uninsured_19_64',
'aggveh',
'pct_no_hins',
'veh_person',
'Total Population in Occupied Housing Units: Renter Occupied',
'Owner Occupied Pop',
'% Renter Pop',
'% Owner Pop',
'Households']
```

[9]:
```
refined_columns = ['Zip Codes',
 'Sum of Less than $100',
 'Sum of $100-$200',
 'Sum of $200-$300',
 'Sum of $300-$400',
 'Sum of $400-$500',
 'Sum of $500-$600',
 'Sum of $600-$700',
 'Sum of $700-$800',
 'Sum of $800-$900',
 'Sum of $900-$1000',
 'Sum of More than $1000',
 'Sum of Total number of delinquent residential accounts',
 'pop',
 'mhhi',
 'pct_black',
 'pct_hisp',
 'pct_asian',
 'pct_povt',
 '% Renter Pop',
 '% Owner Pop',
 'Households']
```

And, let me check my work....

[10]:
```
acs = acs[refined_columns]
```

[11]:
```
acs.head()
```

[11]:
```
   Zip Codes  Sum of Less than $100  Sum of $100-$200  Sum of $200-$300  \
0      90001                 5726.0            4937.0            1582.0
1      90002                 3130.0            2152.0            1052.0
2      90003                 1829.0            1880.0            1562.0
3      90004                 2199.0            1659.0            1119.0
4      90005                 1712.0            1107.0             598.0

   Sum of $300-$400  Sum of $400-$500  Sum of $500-$600  Sum of $600-$700  \
0             684.0             395.0             283.0             220.0
1             708.0             493.0             385.0             343.0
2            1169.0             941.0             782.0             673.0
3             735.0             502.0             387.0             279.0
4             401.0             281.0             175.0             146.0

   Sum of $700-$800  Sum of $800-$900  Sum of $900-$1000  \
0             137.0             132.0               97.0
1             281.0             231.0              201.0
2             513.0             482.0              401.0
```

```
3             223.0             206.0              164.0
4              95.0              95.0               58.0

   Sum of More than $1000  \
0                   709.0
1                  1779.0
2                  3437.0
3                  1116.0
4                   426.0

   Sum of Total number of delinquent residential accounts      pop     mhhi  \
0                                            14902.0       58975.0  38521.0
1                                            10755.0       53111.0  35410.0
2                                            13669.0       72741.0  37226.0
3                                             8589.0       61586.0  48754.0
4                                             5094.0       39479.0  35149.0

   pct_black  pct_hisp  pct_asian      pct_povt  % Renter Pop  % Owner Pop  \
0   0.088648  0.900144   0.002187   0.287523803      0.647257     0.352743
1   0.194950  0.784640   0.006063  0.3286025168      0.621999     0.378001
2   0.221828  0.770542   0.003533  0.3065973854      0.692044     0.307956
3   0.038856  0.511139   0.251437  0.1806014621      0.803900     0.196100
4   0.061374  0.492338   0.350794  0.2805929165      0.912764     0.087236

   Households
0     14174.0
1     13546.0
2     18523.0
3     25192.0
4     18291.0
```

0.1.4 Normalize the Data

So, I'm thinking I might want to make a map that shows the inensity of water bill debt by zip code. This means I need the percentage of the deliquent population each debt "bucket" represents.

I also want to know what percent of the population in each zip code has water bill debt, broadly. To do this, I need to create new columns for each of these columns as a percentage of the deliquent population and total population, respectively.

[12]:
```
list(acs)
```

[12]:
```
['Zip Codes',
 'Sum of Less than $100',
 'Sum of $100-$200',
 'Sum of $200-$300',
 'Sum of $300-$400',
 'Sum of $400-$500',
```

```
'Sum of $500-$600',
'Sum of $600-$700',
'Sum of $700-$800',
'Sum of $800-$900',
'Sum of $900-$1000',
'Sum of More than $1000',
'Sum of Total number of delinquent residential accounts',
'pop',
'mhhi',
'pct_black',
'pct_hisp',
'pct_asian',
'pct_povt',
'% Renter Pop',
'% Owner Pop',
'Households']
```

[13]:
```
acs['Percent Deliquent'] = acs['Sum of Total number of delinquent residential␣
↪accounts']/acs['pop']
acs['Percent Less than $100'] = acs['Sum of Less than $100']/acs['Sum of Total␣
↪number of delinquent residential accounts']
acs['Percent $100 - $200'] = acs['Sum of $100-$200']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent $200 - $300'] = acs['Sum of $200-$300']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent $300 - $400'] = acs['Sum of $300-$400']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent $400 - $500'] = acs['Sum of $400-$500']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent $500 - $600'] = acs['Sum of $500-$600']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent $600 - $700'] = acs['Sum of $600-$700']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent $700 - $800'] = acs['Sum of $700-$800']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent $800 - $900'] = acs['Sum of $800-$900']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent $900 - $1000'] = acs['Sum of $900-$1000']/acs['Sum of Total number␣
↪of delinquent residential accounts']
acs['Percent More than $1000'] = acs['Sum of More than $1000']/acs['Sum of␣
↪Total number of delinquent residential accounts']
```

And, let me check my work….

[14]:
```
acs.head()
```

[14]:
```
  Zip Codes  Sum of Less than $100  Sum of $100-$200  Sum of $200-$300  \
0     90001                 5726.0            4937.0            1582.0
1     90002                 3130.0            2152.0            1052.0
2     90003                 1829.0            1880.0            1562.0
3     90004                 2199.0            1659.0            1119.0
4     90005                 1712.0            1107.0             598.0

   Sum of $300-$400  Sum of $400-$500  Sum of $500-$600  Sum of $600-$700  \
0             684.0             395.0             283.0             220.0
1             708.0             493.0             385.0             343.0
2            1169.0             941.0             782.0             673.0
3             735.0             502.0             387.0             279.0
4             401.0             281.0             175.0             146.0

   Sum of $700-$800  Sum of $800-$900  Sum of $900-$1000  \
0             137.0             132.0               97.0
1             281.0             231.0              201.0
2             513.0             482.0              401.0
3             223.0             206.0              164.0
4              95.0              95.0               58.0

   Sum of More than $1000  \
0                   709.0
1                  1779.0
2                  3437.0
3                  1116.0
4                   426.0

   Sum of Total number of delinquent residential accounts      pop     mhhi  \
0                                            14902.0       58975.0  38521.0
1                                            10755.0       53111.0  35410.0
2                                            13669.0       72741.0  37226.0
3                                             8589.0       61586.0  48754.0
4                                             5094.0       39479.0  35149.0

   pct_black  pct_hisp  pct_asian      pct_povt  % Renter Pop  % Owner Pop  \
0   0.088648  0.900144   0.002187   0.287523803      0.647257     0.352743
1   0.194950  0.784640   0.006063  0.3286025168      0.621999     0.378001
2   0.221828  0.770542   0.003533  0.3065973854      0.692044     0.307956
3   0.038856  0.511139   0.251437  0.1806014621      0.803900     0.196100
4   0.061374  0.492338   0.350794  0.2805929165      0.912764     0.087236

   Households  Percent Deliquent  Percent Less than $100  Percent $100 - $200  \
0     14174.0           0.252683                0.384244             0.331298
1     13546.0           0.202500                0.291027             0.200093
2     18523.0           0.187913                0.133806             0.137537
3     25192.0           0.139464                0.256025             0.193154
```

```
4     18291.0          0.129031                0.336082            0.217314

   Percent $200 - $300  Percent $300 - $400  Percent $400 - $500  \
0             0.106160             0.045900             0.026507
1             0.097815             0.065830             0.045839
2             0.114273             0.085522             0.068842
3             0.130283             0.085575             0.058447
4             0.117393             0.078720             0.055163

   Percent $500 - $600  Percent $600 - $700  Percent $700 - $800  \
0             0.018991             0.014763             0.009193
1             0.035797             0.031892             0.026127
2             0.057210             0.049235             0.037530
3             0.045058             0.032483             0.025963
4             0.034354             0.028661             0.018649

   Percent $800 - $900  Percent $900 - $1000  Percent More than $1000
0             0.008858              0.006509                 0.047578
1             0.021478              0.018689                 0.165411
2             0.035262              0.029336                 0.251445
3             0.023984              0.019094                 0.129934
4             0.018649              0.011386                 0.083628
```

Looks like it worked!

0.1.5 Summary Statistics

Now that my data is cleaned and normalized, I want to get a better sense of how it looks. I'll calculate some summary stats.

[15]:
```
acs['Percent Deliquent'].describe()
```

[15]:
```
count    1020.000000
mean        0.052453
std         0.381212
min         0.000000
25%         0.005332
50%         0.017357
75%         0.045156
max        11.881386
Name: Percent Deliquent, dtype: float64
```

It seems that on average, about 5% of people per zip code have some level of water bill debt, with the median hovering around 1.7%. This suggests there are some outliers on the larger end that are pulling the average up higher. There are probably some zip codes that have a very high percentage of residental accounts with debt, and these are impacting the overall average. Hopefully my later analysis can shed some light on where these higher-level debt zip codes are.

I'm going to go ahead and look at summary stats for each of the bucketed debt levels; however, since there are so many buckets, I am going to combine them into 1 table for key stats (mean and median).

[16]:
```
acs[['Percent Deliquent',
 'Percent Less than $100',
 'Percent $100 - $200',
 'Percent $200 - $300',
 'Percent $300 - $400',
 'Percent $400 - $500',
 'Percent $500 - $600',
 'Percent $600 - $700',
 'Percent $700 - $800',
 'Percent $800 - $900',
 'Percent $900 - $1000',
 'Percent More than $1000']].mean()
```

[16]:
```
Percent Deliquent           0.052453
Percent Less than $100      0.269824
Percent $100 - $200         0.241373
Percent $200 - $300         0.142088
Percent $300 - $400         0.098082
Percent $400 - $500         0.230112
Percent $500 - $600         0.045637
Percent $600 - $700         0.036646
Percent $700 - $800         0.027409
Percent $800 - $900         0.022396
Percent $900 - $1000        0.018324
Percent More than $1000     0.113338
dtype: float64
```

[17]:
```
acs[['Percent Deliquent',
           'Percent Less than $100',
           'Percent $100 - $200',
           'Percent $200 - $300',
           'Percent $300 - $400',
           'Percent $400 - $500',
           'Percent $500 - $600',
           'Percent $600 - $700',
           'Percent $700 - $800',
           'Percent $800 - $900',
           'Percent $900 - $1000',
           'Percent More than $1000']].median()
```

[17]:
```
Percent Deliquent           0.017357
Percent Less than $100      0.233190
Percent $100 - $200         0.214128
Percent $200 - $300         0.121451
```

```
Percent $300 - $400        0.078720
Percent $400 - $500        0.053389
Percent $500 - $600        0.038719
Percent $600 - $700        0.029613
Percent $700 - $800        0.020958
Percent $800 - $900        0.016476
Percent $900 - $1000       0.011659
Percent More than $1000    0.054545
dtype: float64
```

So, this is a lot of information, but I have noticed some interesting trends….

So, the bucket with the greatest percentage of deliquent accounts, on average per zip code, was less than 100 (at 23.3%). The next highest bucket was between 100 and 200, a t 21.4%. This means that, on average, across zip codes, most debt-holders had debt on the lower end (less than $200).

However, we can also tell from the mean vs median values that there is a slight skew in the percentages themselves. It is also worth mentioning that there are espeically high outliers in the 400-500 bucket (with the mean at 23 percent and the median at 5.3 percent). Overall, this suggests that there are certain zip codes wherein these values make up a higher percentage of the total debt.

More broadly, in the context of the 'Percent Deliquent' bucket, this skew means that, there are certain zip codes within each bucket that might act as outliers that make up especially large percentages of water bill debt. This relfects unequal distribution of debt across zip codes. This may be due to other factors such as median household income, race and ethnicity, or owner v renter status. We may get a sense of where these zip codes lie as we further map the data.

How many total households have some level of water bill debt, though?

[18]:
```
acs['Sum of Total number of delinquent residential accounts'].sum(axis = 0,␣
↪skipna = True)
```

[18]:
```
2897402.00000002
```

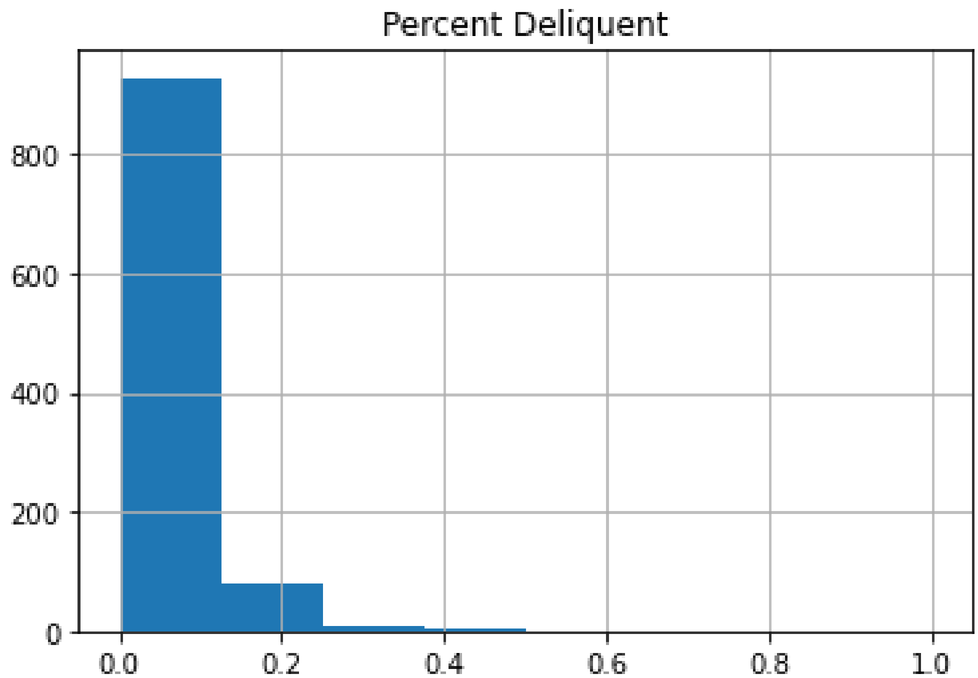
In total, 2,897,402 households in the state (as reported in the survey) have some level of water debt, and based on my summary stats, it seems that the values are fairly evently distributed across the state.

0.1.6 Data Visualization

I think it will be a little bit easier to visualize what is happeneing with the debt data if I put it in a histogram. First, I am going to do that with the total percentage of deliquent accounts.

[19]:
```
acs.hist(column = 'Percent Deliquent', bins = 8, range=(0, 1))
```

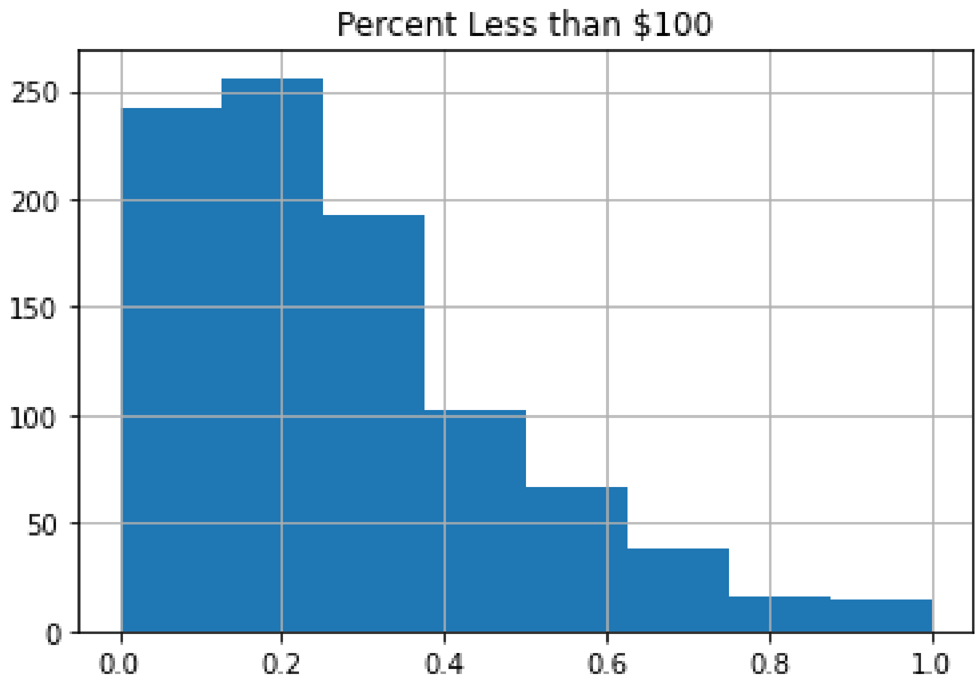
[19]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd185909bb0>]],
      dtype=object)
```



As expected from my summary stats, we can see the vast majority of %Deliquent accounts are centered at 1% of the population. However, there are a few outliers closer to 5%, and it will be interesting to see if there is any relationship with other demographic factors once we get into mapping.

[20]:
```
acs.hist(column = 'Percent Less than $100', bins = 8, range=(0, 1))
```

[20]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd1857e6e50>]],
      dtype=object)
```

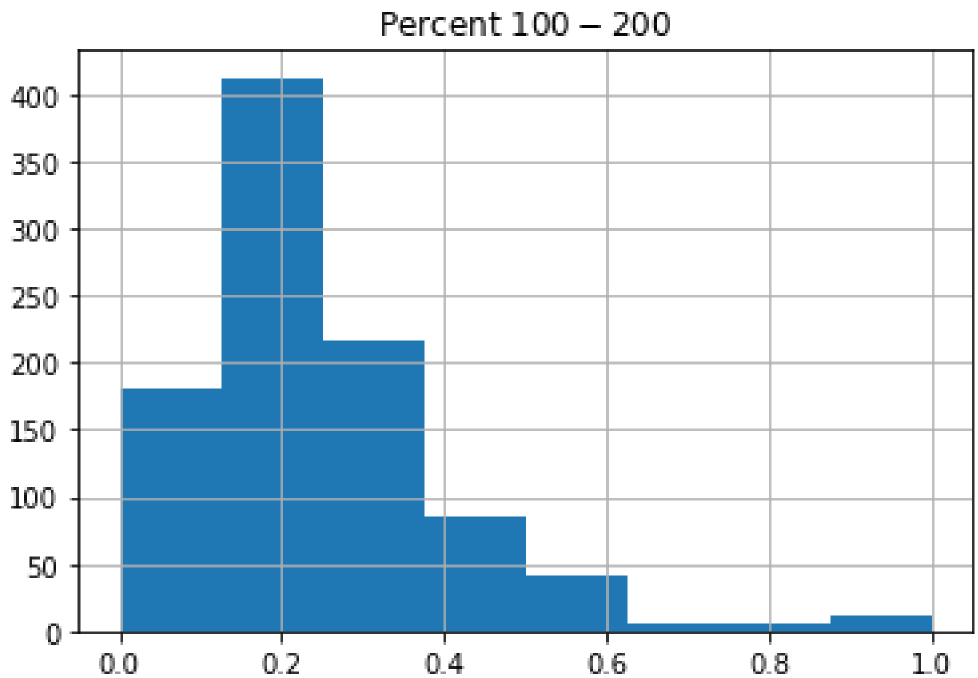


The distribution of Percent Less than $100 is much more pronounced. From this histogram, you can see that the percentage of deliquent accounts (whose debt is less than 100) varies across zip codes: it can make up anywhere from 0 to 100 percent of the deliquent accounts across zip codes.

Let's look at the distribution across the other buckets, just to get a sense of their spread.

[21]:
```
acs.hist(column = 'Percent $100 - $200', bins = 8, range=(0, 1))
```

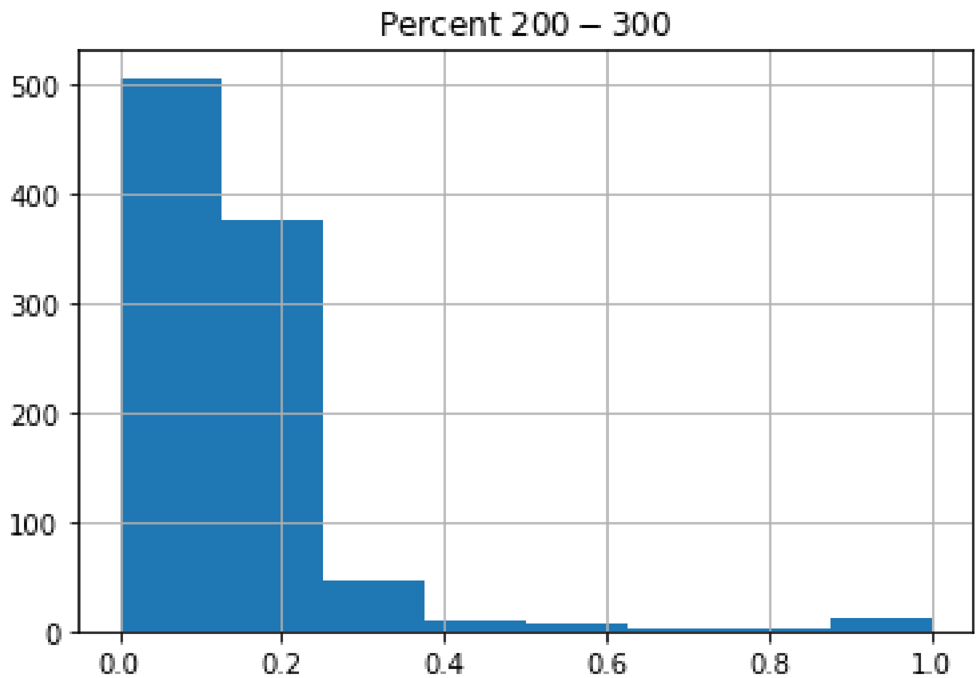
[21]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd1857d34f0>]],
      dtype=object)
```



There is a large peak with this bucket around 20%, which is reflected in the median and the mean.

[22]:
```
acs.hist(column = 'Percent $200 - $300', bins = 8, range=(0, 1))
```

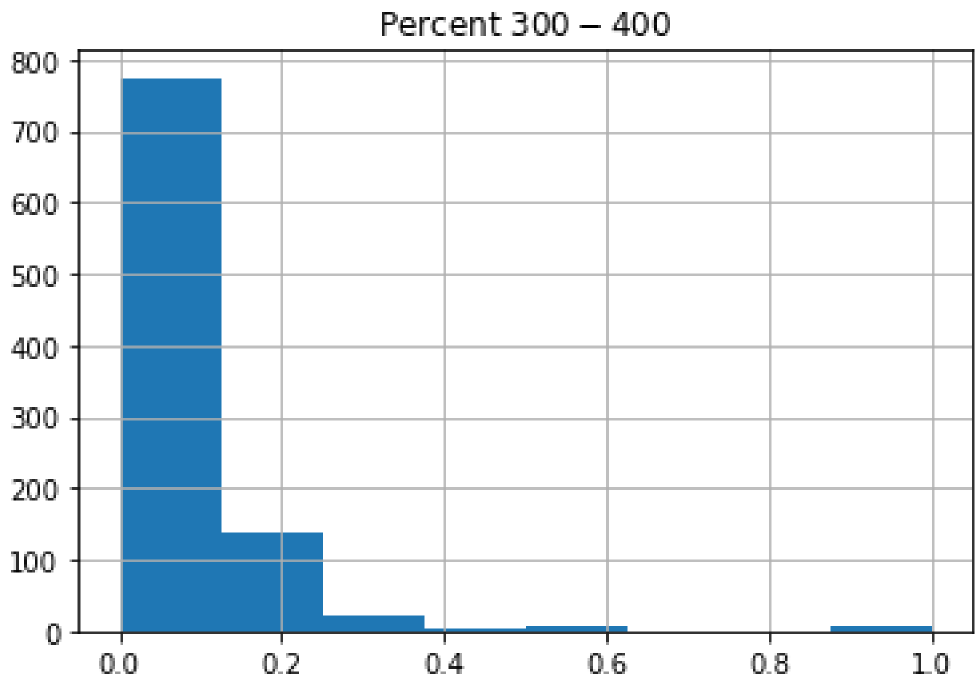
[22]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd184eef220>]],
      dtype=object)
```



There is a skew in this bucket between 0 - 10%

[23]:
```
acs.hist(column = 'Percent $300 - $400', bins = 8, range=(0, 1))
```

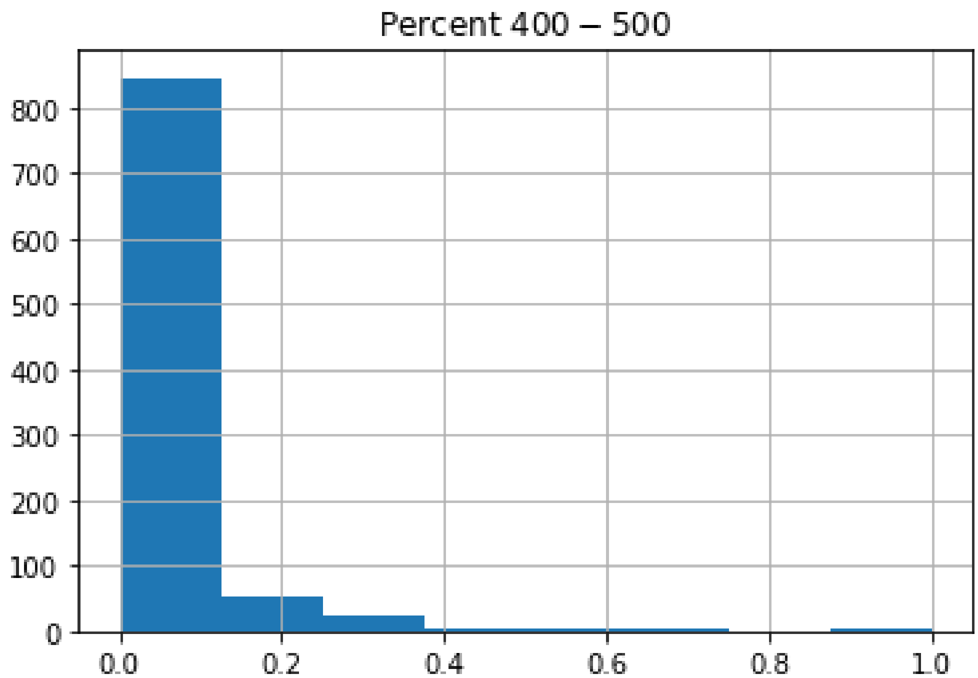
[23]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd185ab9c70>]],
      dtype=object)
```



Again, a skew here between 0-10%

[24]:
```
acs.hist(column = 'Percent $400 - $500', bins = 8, range=(0, 1))
```

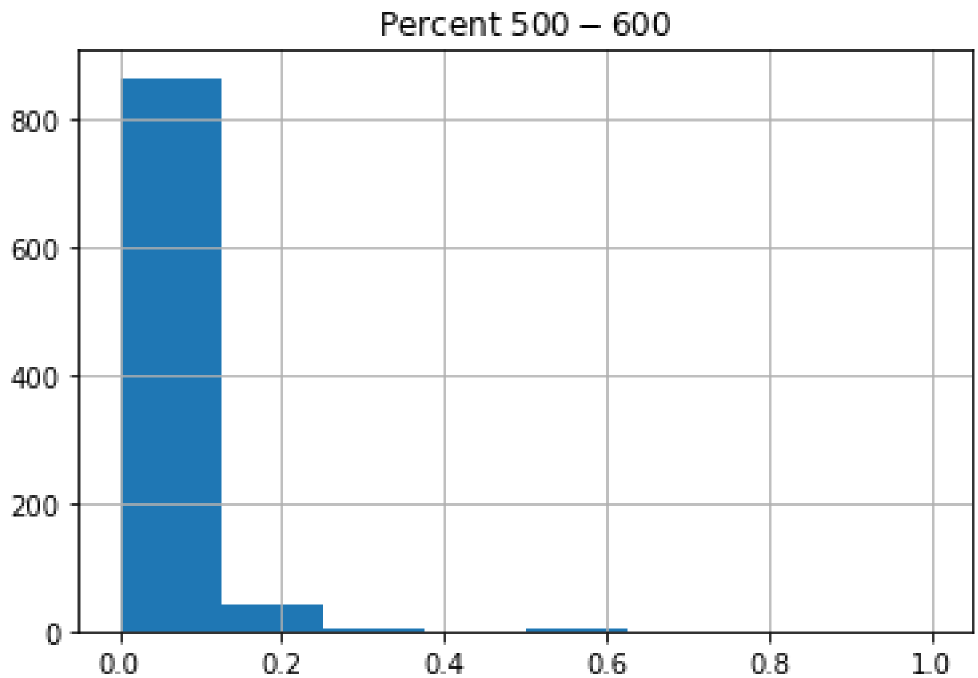
[24]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd184e7e700>]],
      dtype=object)
```



Similar skew among this data... with a few outliers around 60-70% and 90-100%

[25]:
```
acs.hist(column = 'Percent $500 - $600', bins = 8, range=(0, 1))
```

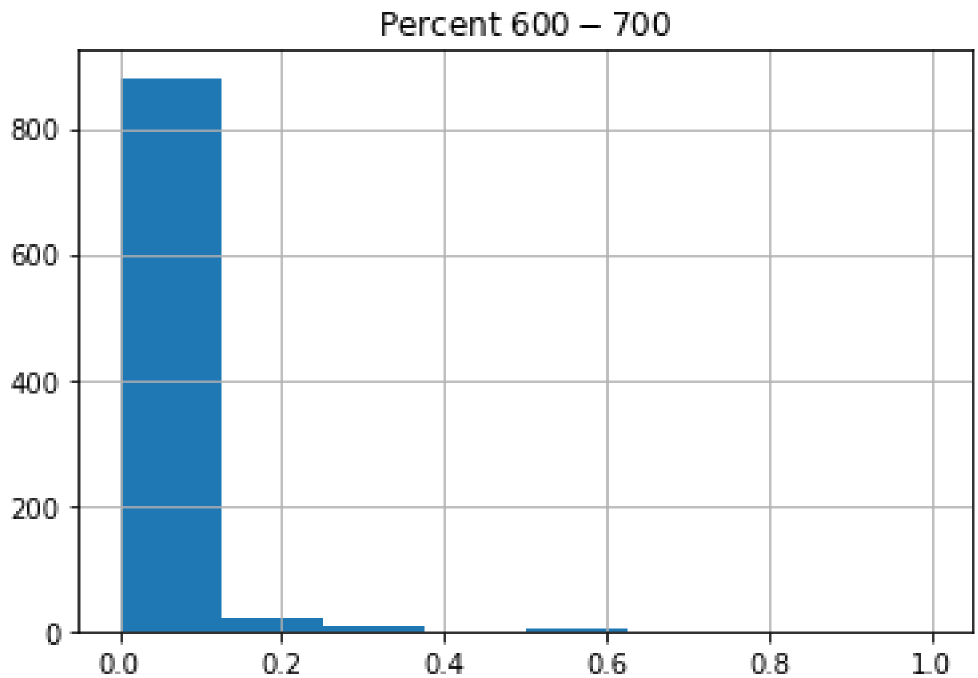
[25]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd184ddd040>]],
      dtype=object)
```



Similar skew here as well, which is to be expected given the median/mode values.

[26]:
```
acs.hist(column = 'Percent $600 - $700', bins = 8, range=(0, 1))
```

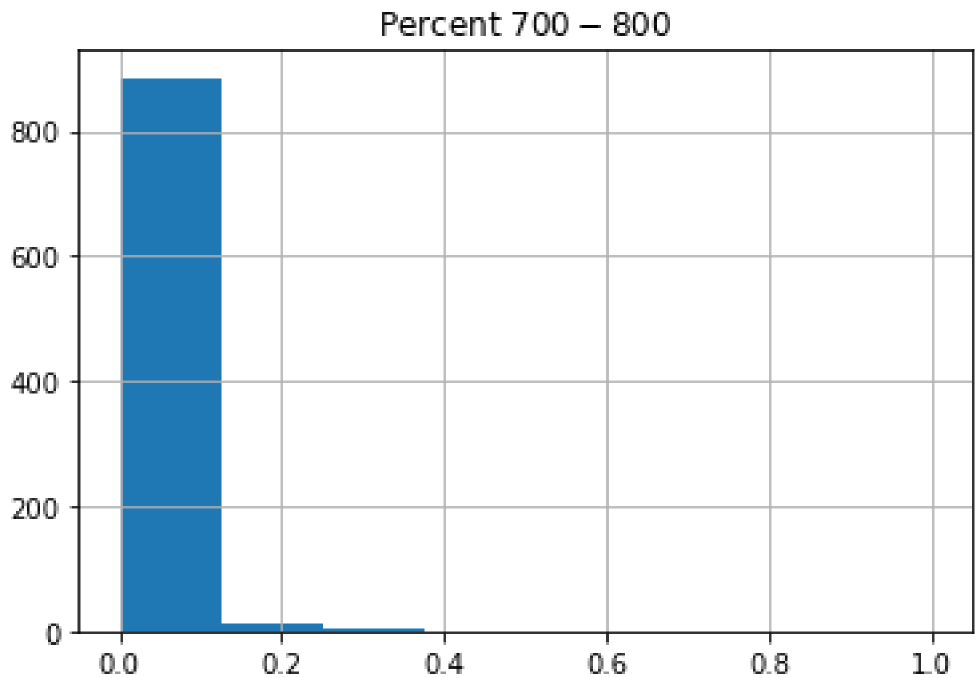
[26]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd184d9c400>]],
      dtype=object)
```



And again, similar skew here as well, which is to be expected given the median/mode values.

[27]:
```
acs.hist(column = 'Percent $700 - $800', bins = 8, range=(0, 1))
```

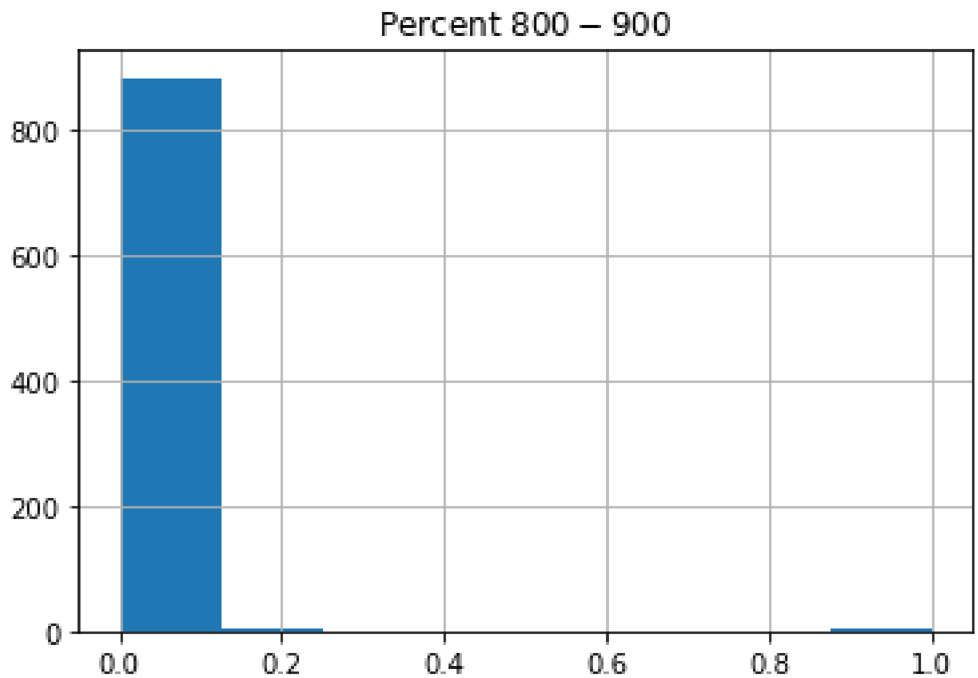
[27]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd184d61670>]],
      dtype=object)
```



Again, a similar skew here.

[28]:
```
acs.hist(column = 'Percent $800 - $900', bins = 8, range=(0, 1))
```

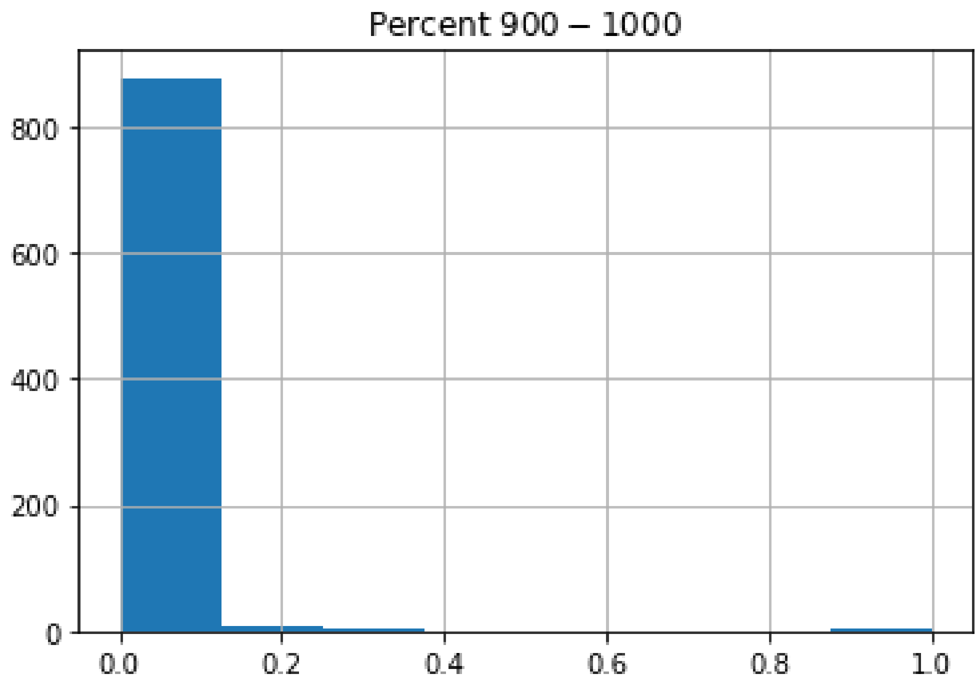
[28]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd184d21dc0>]],
      dtype=object)
```



..and here. Though there is an interesting outlier near 90-100%

[29]:
```
acs.hist(column = 'Percent $900 - $1000', bins = 8, range=(0, 1))
```

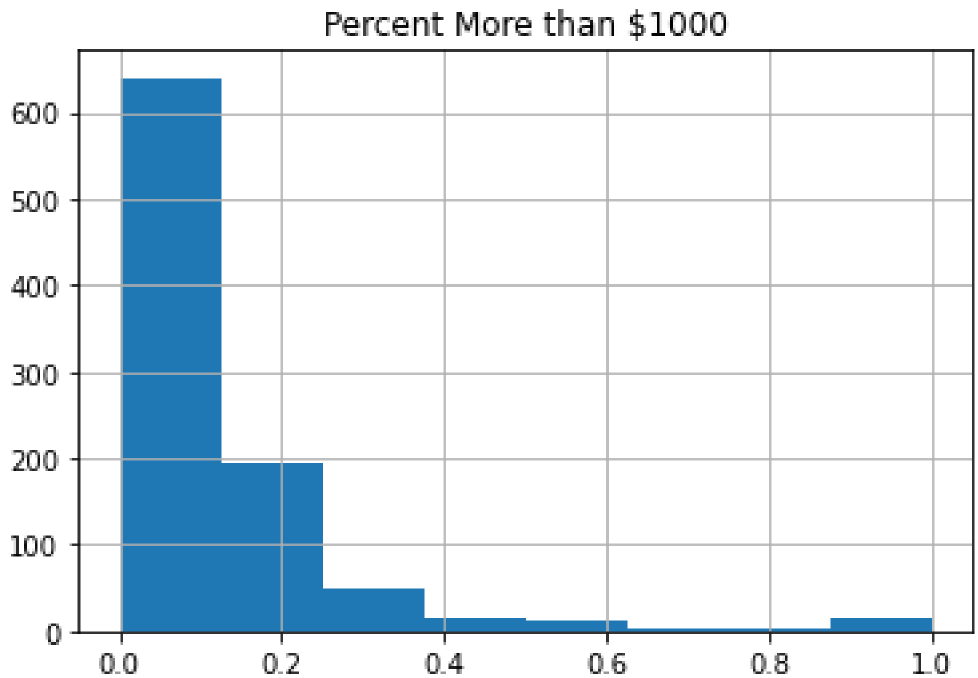
[29]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd184cd47f0>]],
      dtype=object)
```



And here... with a notable outlier near 90-100%. This might be interesting if it comes up during the mapping.

[30]:
```
acs.hist(column = 'Percent More than $1000', bins = 8, range=(0, 1))
```

[30]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fd184c59dc0>]],
      dtype=object)
```



There is a much larger spread in this data, and again, with some outliers near 90-100% which is quite concerning.

Essentially, we can see from all of these historgrams that, for the most part, the debt buckets are centered near 0-10 percent and some peaks around 20%. There are, however, some outliers around 8-100 percent. This suggests that in some zip codes all of the household debt is contained within that debt bucket. For some of the higher buckets (i.e. greater than 1000, that is expecially concerning).

0.1.7 Incorporation of Demographics

Now that we have a sense of how the debt is distributed, it is time to incorporate some demographic information in the form of scatterplots. The purpose here is to detect some trends in the data between the total percentage of deliquent households in a given zip code and our demographic factors of interest (median household income, %hispanic, %black, or percent poverty)

[31]:
```
px.scatter(acs,
           x ='mhhi',
           y = 'Percent Deliquent')
```

We can see that many of the deliquent households have a median household income between 20,000 and 100,000. As income increases, we can tell that the percentage of deliquent households becomes much more sparse and in all of these higher income cases, the percentage of deliquent households is extremely small (centered around 0).

Notably, there are some outliers in this dataset. In particluar, the dot at 12 on the y axis and at 2. I think these datapoints should be removed, as they are clearly mistakes since they equal over

100%.

[32]:
```
acs.drop(acs[acs['Percent Deliquent'] > 1].index, inplace = True)
```

[33]:
```
px.scatter(acs,
           x ='mhhi',
           y = 'Percent Deliquent')
```

Now we can get a much better sense of the trend in the data - there is a very high conentration of zip codes with some degree of water bill debt between 30,000 and 100,000. This is a clear trend in the data, wherein lower income zip codes tend to have more water bill debt than higher income zip codes.

Now let's see if there are trends in the other demographic factors.

[34]:
```
px.scatter(acs,
           x ='pct_povt',
           y = 'Percent Deliquent')
```

Looking at the percentage of poverty, there is not necessarily a clear trend. There are definitely a high conentration of deliquent households in zip codes with poverty levels between 10-20%. However, when we dive deeper into this data, there might be a clerer trend.

The poverty rate in the US is around 12%, so if we condier anything higher than 12% as a high poverty area, there is some indication that there are a high concentration of zip codes with some degree of deliquency on their bills in moderately-high poverty rate zip codes. Of course, there needs to be bit more examination of the data before we make a clearer judgement call.

[35]:
```
px.scatter(acs,
           x ='pct_black',
           y = 'Percent Deliquent')
```

There is a very slight trend here, but not a very obvious one. There are some zip codes with a higher percentage of Black populations that have higher bill debt (as you can see on the right hand side of the scatterplot). However, more analysis is needed.

[36]:
```
px.scatter(acs,
           x ='pct_hisp',
           y = 'Percent Deliquent')
```

It definitely seems like there are many more datapoints with a larger hispanic population than black population. It also does appear that populations with a greater percentage of hispanic populations also have fairly high levels of water bill debt deliqiency. I think more analysis should be done, but there seems to be a clearer trend in this data than with the % black population.

Since I am running out of memory, I will continue in a new notebook with my maps.