Causal_Effect_Race_Eviction

July 30, 2018

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn import linear_model
import xgboost as xgb
import matplotlib.ticker
from sklearn import metrics
from sklearn import preprocessing
matplotlib.rcParams.update({'font.size': 16})
%matplotlib inline
pd.options.display.max_columns = 100
```

In [2]:
```
# df = pd.read_csv("data/block-groups.csv")
df = pd.read_csv("data/counties_US.csv")
#df = pd.read_csv("data/cities_US.csv")
```

In [3]:
```
df.dropna(axis=0, how='any', inplace=True)
#print(df.iloc[0])
columns = df.columns
renames = {}
for col in columns:
    renames[col] = col.replace('-', '_')
df = df.rename(columns=renames)
df.describe()
```

Out[3]:

	GEOID	year	population	poverty_rate \
count	41299.000000	41299.000000	4.129900e+04	41299.000000
mean	30928.597956	2008.187753	9.717697e+04	12.410998
std	14754.405831	4.819986	3.287348e+05	5.813251
min	1001.000000	2000.000000	6.700000e+01	0.000000
25%	19089.000000	2004.000000	1.044500e+04	8.300000
50%	29181.000000	2008.000000	2.351300e+04	11.460000
75%	45086.000000	2012.000000	6.268300e+04	15.315000
max	56045.000000	2016.000000	1.003839e+07	45.380000

	pct_renter_occupied	median_gross_rent	median_household_income	\
count	41299.000000	41299.000000	41299.000000	
mean	26.820699	592.652970	42136.557350	
std	7.648861	189.157504	11524.034138	
min	7.350000	178.000000	9333.000000	
25%	21.740000	464.000000	34202.000000	
50%	25.540000	571.000000	40657.000000	
75%	30.430000	680.000000	48007.000000	
max	100.000000	1827.000000	123453.000000	

	median_property_value	rent_burden	pct_white	pct_af_am	\
count	4.129900e+04	41299.000000	41299.000000	41299.000000	
mean	1.164624e+05	26.821584	79.966203	8.409063	
std	7.300267e+04	4.754268	18.957256	14.113073	
min	0.000000e+00	8.300000	2.860000	0.000000	
25%	7.470000e+04	23.600000	69.460000	0.420000	
50%	9.640000e+04	26.800000	87.330000	1.810000	
75%	1.363000e+05	29.800000	94.790000	9.250000	
max	1.000001e+06	50.100000	100.000000	86.760000	

	pct_hispanic	pct_am_ind	pct_asian	pct_nh_pi	pct_multiple	\
count	41299.000000	41299.000000	41299.000000	41299.000000	41299.000000	
mean	7.861583	1.186445	0.994529	0.063298	1.431872	
std	13.083396	4.495723	2.096220	0.611061	1.426454	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.310000	0.140000	0.190000	0.000000	0.710000	
50%	2.810000	0.270000	0.430000	0.010000	1.130000	
75%	7.620000	0.580000	0.920000	0.040000	1.710000	
max	95.680000	84.960000	45.260000	48.300000	23.490000	

	pct_other	renter_occupied_households	eviction_filings	\
count	41299.000000	4.129900e+04	41299.000000	
mean	0.087025	1.301934e+04	892.026490	
std	0.150616	5.425438e+04	4419.432913	
min	0.000000	5.000000e+00	0.000000	
25%	0.000000	9.710000e+02	5.000000	
50%	0.040000	2.315000e+03	37.000000	
75%	0.110000	6.844500e+03	240.000000	
max	4.900000	1.792186e+06	143753.000000	

	evictions	eviction_rate	eviction_filing_rate	imputed	\
count	41299.000000	41299.000000	41299.000000	41299.000000	
mean	374.336449	1.678239	3.201757	0.014819	
std	1543.484514	1.977446	5.027240	0.120828	
min	0.000000	0.000000	0.000000	0.000000	
25%	3.000000	0.320000	0.490000	0.000000	
50%	25.000000	1.110000	1.630000	0.000000	
75%	140.000000	2.320000	3.800000	0.000000	

```
max    47716.000000      24.160000            118.620000      1.000000

             subbed
count  41299.000000
mean       0.015860
std        0.124935
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000
```

In [4]:
```
df.head()
```

Out[4]:
```
   GEOID  year            name parent_location  population  poverty_rate  \
0   1001  2000  Autauga County         Alabama     43671.0         10.92
1   1003  2000  Baldwin County         Alabama    140415.0         10.15
2   1005  2000  Barbour County         Alabama     29038.0         26.80
3   1007  2000     Bibb County         Alabama     20826.0         20.61
5   1011  2000  Bullock County         Alabama     11714.0         33.48

   pct_renter_occupied  median_gross_rent  median_household_income  \
0                19.21              537.0                  42013.0
1                20.46              566.0                  40250.0
2                26.87              333.0                  25101.0
3                19.81              348.0                  31420.0
5                25.51              324.0                  20605.0

   median_property_value  rent_burden  pct_white  pct_af_am  pct_hispanic  \
0                94800.0         22.6      79.74      17.01          1.40
1               122500.0         24.5      86.08      10.22          1.76
2                68600.0         25.1      50.93      46.04          1.65
3                74600.0         22.9      76.20      22.01          1.01
5                56600.0         35.1      23.60      72.44          2.75

   pct_am_ind  pct_asian  pct_nh_pi  pct_multiple  pct_other  \
0        0.43       0.44       0.03          0.86       0.10
1        0.54       0.38       0.03          0.93       0.07
2        0.41       0.29       0.02          0.66       0.01
3        0.22       0.08       0.01          0.47       0.00
5        0.32       0.18       0.01          0.66       0.05

   renter_occupied_households  eviction_filings  evictions  eviction_rate  \
0                      3074.0              61.0       40.0           1.30
1                     11320.0             213.0       65.0           0.57
2                      2797.0              15.0       11.0           0.39
3                      1470.0              13.0        8.0           0.54
5                      1012.0               7.0        6.0           0.59
```

```
   eviction_filing_rate  imputed  subbed
0                  1.98      0.0     0.0
1                  1.88      0.0     0.0
2                  0.54      0.0     0.0
3                  0.88      0.0     0.0
5                  0.69      0.0     0.0
```

1 Causal Inference: Using Propensity modeling to estimate race causal effect on evictions.

Propensity score methods have become one of the most important tools for analyzing causal effects in observational studies.

step 1: select features: 'poverty_rate','rent_burden','pct_renter_occupied','renter_occupied_households','med

step 2: build a probabilistic model to predict the percentage of percentage of black race in a city, the predicted value is called propensity score.

step 3: divide the propensity scores into several buckets.

step 4: compare the correlation of eviction rates with percentage of back race within each buckets.

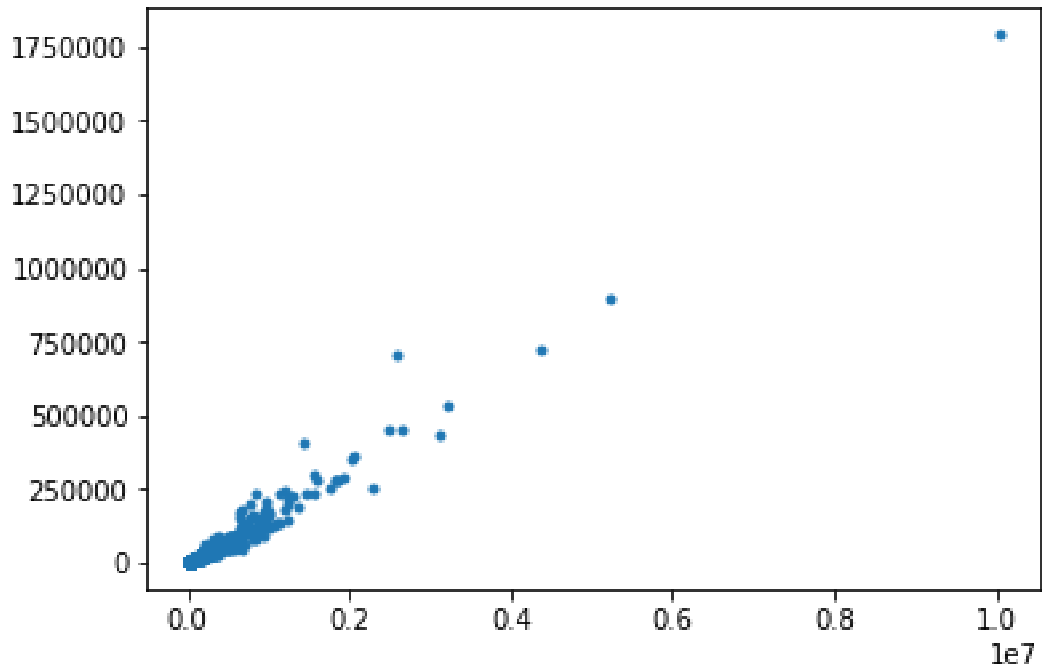
```
In [5]: df_16 = df[df.year == 2016]
        df_16.shape
```

```
Out[5]: (2493, 26)
```

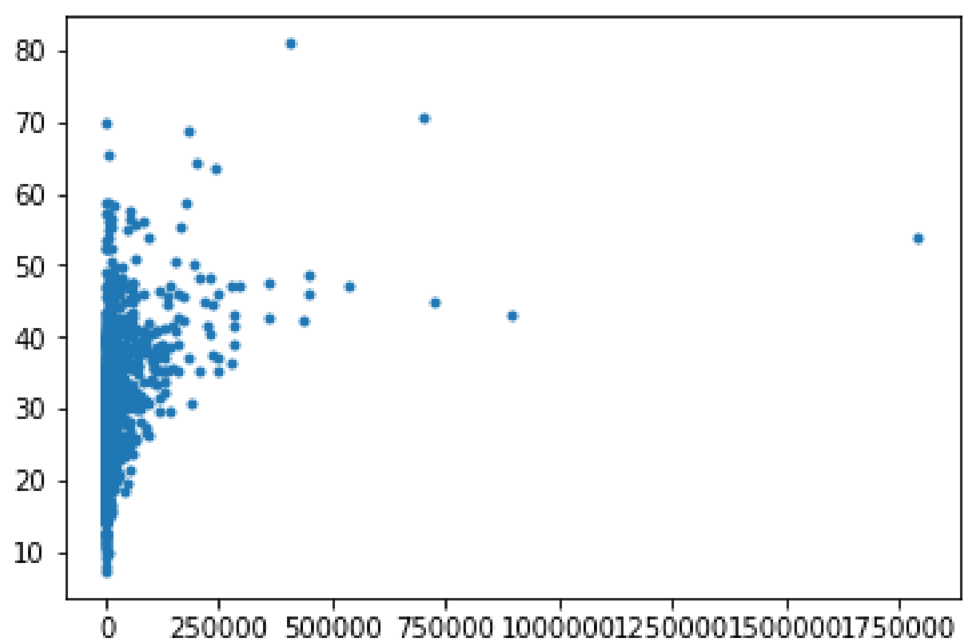
```
In [6]: df_16.reset_index(inplace = True)
```

```
In [7]: plt.plot(df_16.population, df_16.renter_occupied_households,'.')
```

```
Out[7]: [<matplotlib.lines.Line2D at 0x10df9d128>]
```

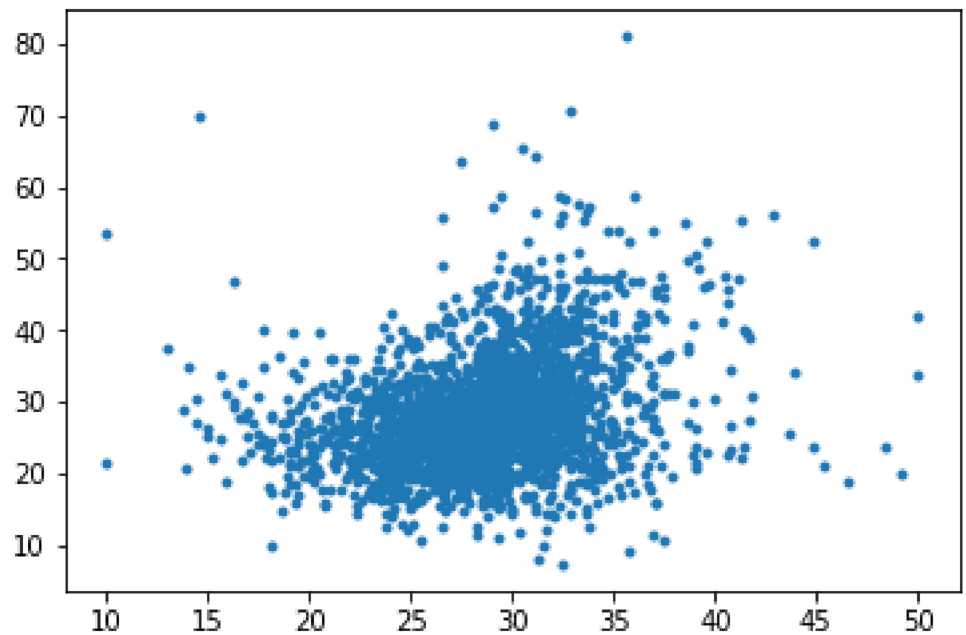



```
In [8]: plt.plot(df_16.renter_occupied_households, df_16.pct_renter_occupied,'.')

Out[8]: [<matplotlib.lines.Line2D at 0x10ed4c6a0>]
```



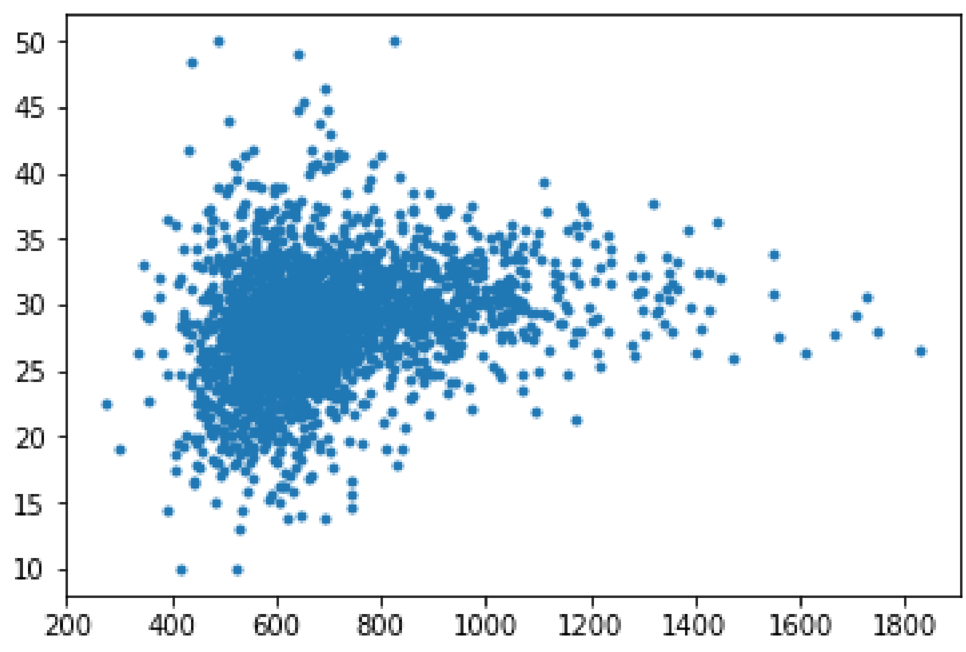
```
In [9]: plt.plot(df_16.rent_burden, df_16.pct_renter_occupied,'.')
```

```
Out[9]: [<matplotlib.lines.Line2D at 0x10ee0beb8>]
```



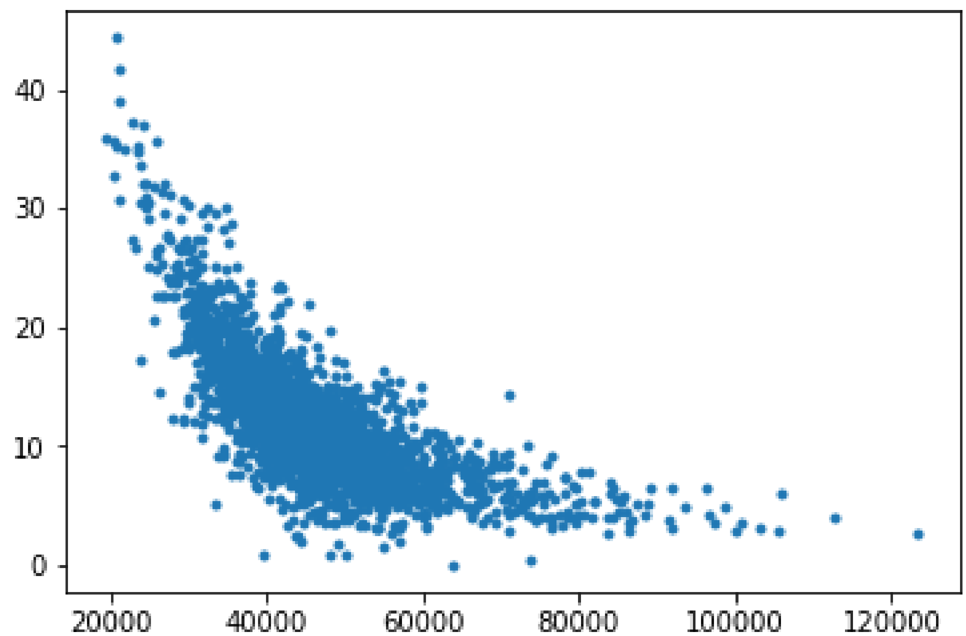

```
In [10]: plt.plot(df_16.median_gross_rent, df_16.rent_burden,'.')
```

```
Out[10]: [<matplotlib.lines.Line2D at 0x10ee4d048>]
```



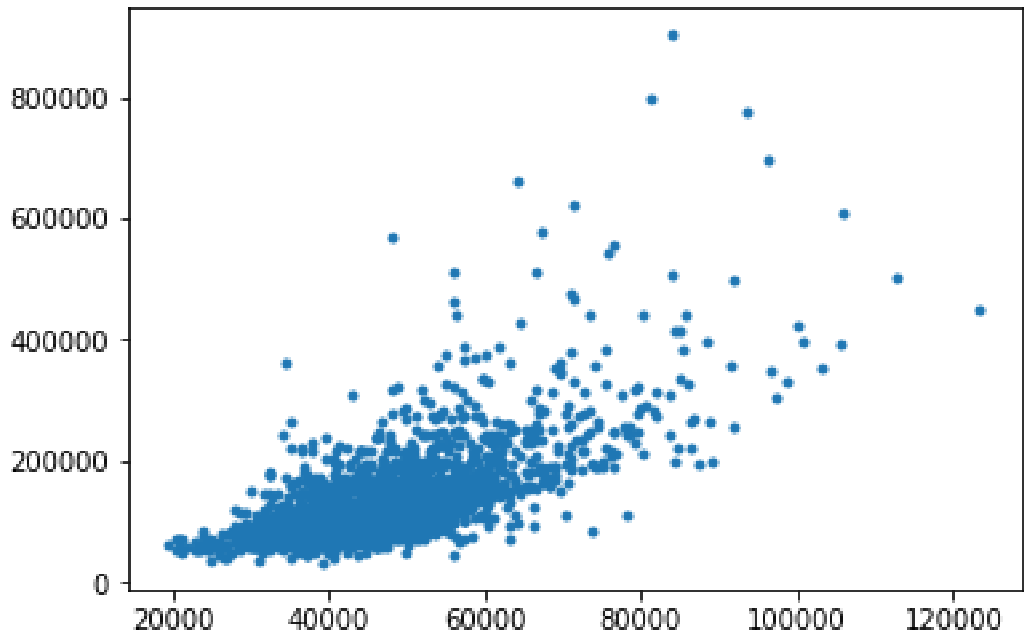
```
In [11]: plt.plot(df_16.median_household_income, df_16.poverty_rate, '.')
```

```
Out[11]: [<matplotlib.lines.Line2D at 0x111ae0cc0>]
```




```
In [12]: plt.plot(df_16.median_household_income, df_16.median_property_value,'.')
```

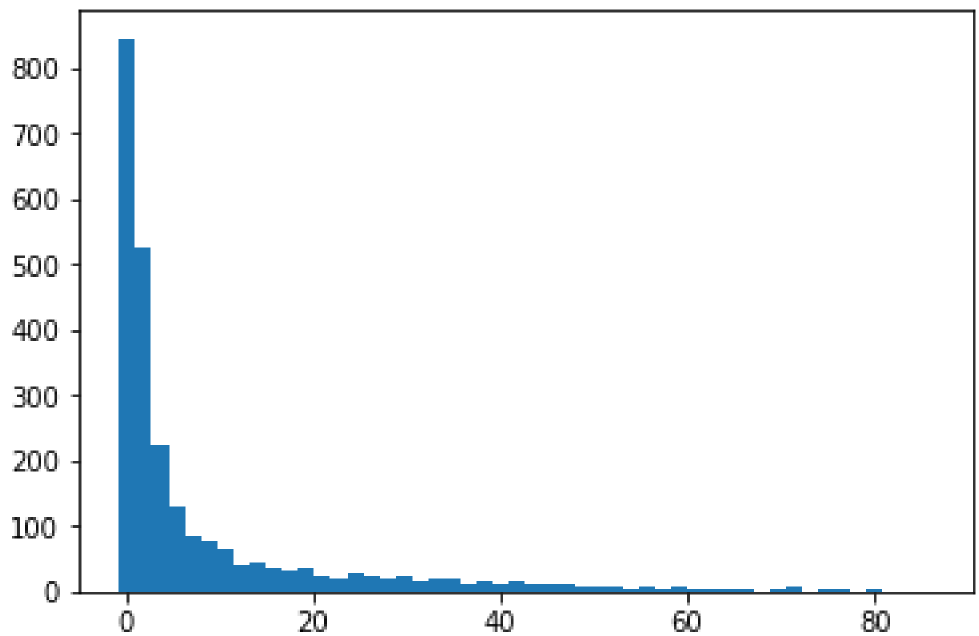
```
Out[12]: [<matplotlib.lines.Line2D at 0x111b60908>]
```




```
In [13]: df_16dummy = pd.get_dummies(df_16.parent_location)

In [14]: # df_16norm = pd.DataFrame(2000*preprocessing.normalize(df_16[['renter_occupied_house
         #                                                           'median_property_value'
         #                          columns = ['renter_occupied_households','median_gross_rent

         # df_16[['poverty_rate','rent_burden','pct_renter_occupied']].shape

         # #del X

         # X = pd.concat([df_16[['poverty_rate','rent_burden','pct_renter_occupied']], df_16no

In [15]: df_16norm = pd.DataFrame(preprocessing.normalize(df_16[['poverty_rate','rent_burden',
                                                                 'median_property_value']]
                                    columns = ['poverty_rate','rent_burden','pct_renter_occupied

         X = pd.concat([df_16norm, df_16dummy], axis = 1)

In [16]: #np.finfo(float).eps

In [17]: #del df_16

In [18]: #df_16 = df_16.copy()
         #df_16.loc[df_16.pct_af_am == 0 , 'pct_af_am'] = np.finfo(float).eps

In [19]: #df_16.loc[df_16.pct_af_am == 1 , 'pct_af_am'] = 1+np.finfo(float).eps
```

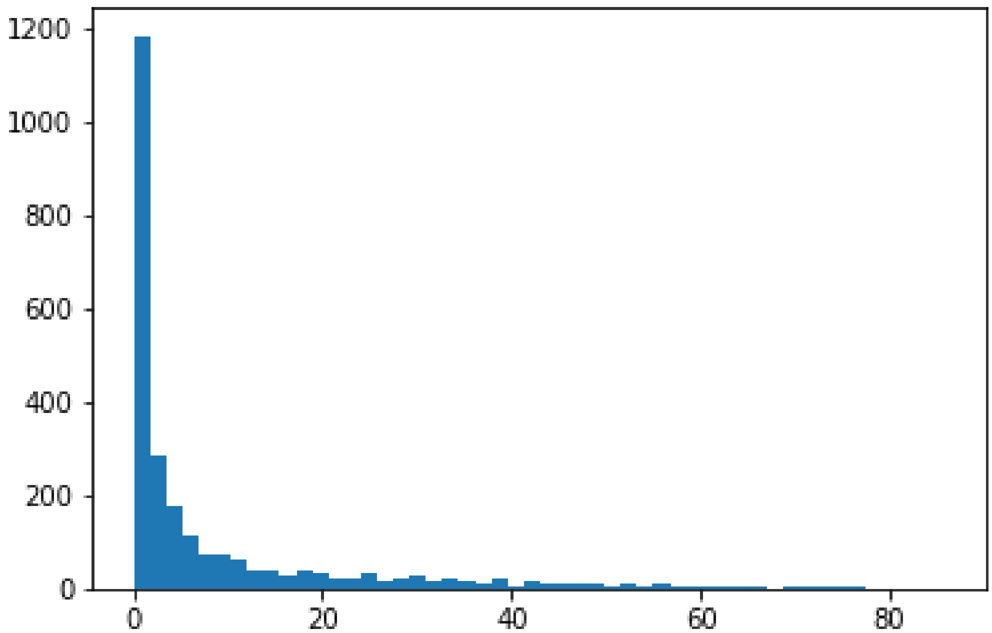
```
In [20]: df_16.pct_af_am.describe()

Out[20]: count    2493.000000
         mean        8.639996
         std        14.175599
         min         0.000000
         25%         0.560000
         50%         2.030000
         75%         9.550000
         max        85.950000
         Name: pct_af_am, dtype: float64

In [21]: #y = df_16['pct_af_am'].apply(lambda x: np.log(x/(1.-x)))

In [22]: #y = df_16['pct_af_am'].apply(lambda x: np.log(x/(100-x)))

In [23]: y = df_16['pct_af_am']

In [24]: model = xgb.XGBRegressor(max_depth=6, learning_rate=0.5, n_estimators=100, silent=Tru
                                  booster='gbtree', n_jobs=1, nthread=None, gamma=0, min_child_
                                  subsample=1, colsample_bytree=1, colsample_bylevel=1, reg_alp
                                  scale_pos_weight=1, base_score=0.5, random_state=0, seed=None

In [25]: #xgb.XGBRegressor?

In [26]: # model = linear_model.SGDRegressor(loss='squared_epsilon_insensitive', penalty='elas
         #                                   fit_intercept=True,max_iter=6000, tol=None, shuff
         #                                   random_state=42, learning_rate='invscaling', eta0
         #                                   warm_start=False,average=False)

In [27]: #model = linear_model.LinearRegression()
         model.fit(X,y)
         y_pred = model.predict(X)

         metrics.explained_variance_score(y, y_pred)

Out[27]: 0.9980999669639864

In [28]: #linear_model.SGDRegressor?

In [29]: metrics.r2_score(y, y_pred)

Out[29]: 0.998099966863387

In [30]: plt.hist(y_pred,bins = 50 )

Out[30]: (array([845., 524., 223., 128.,  84.,  76.,  65.,  38.,  44.,  34.,  32.,
                  35.,  24.,  20.,  29.,  25.,  18.,  25.,  17.,  19.,  20.,  13.,
                  17.,  10.,  16.,  11.,  10.,  11.,   9.,   6.,   7.,   4.,   7.,
                   5.,   8.,   5.,   2.,   3.,   2.,   1.,   5.,   6.,   1.,   3.,
```

```
         2.,    0.,    2.,    0.,    1.,    1.]),
 array([-0.67446256,  1.06185995,  2.79818245,  4.53450495,  6.27082746,
         8.00714996,  9.74347246, 11.47979496, 13.21611747, 14.95243997,
        16.68876247, 18.42508498, 20.16140748, 21.89772998, 23.63405249,
        25.37037499, 27.10669749, 28.84302   , 30.5793425 , 32.315665  ,
        34.0519875 , 35.78831001, 37.52463251, 39.26095501, 40.99727752,
        42.73360002, 44.46992252, 46.20624503, 47.94256753, 49.67889003,
        51.41521254, 53.15153504, 54.88785754, 56.62418005, 58.36050255,
        60.09682505, 61.83314755, 63.56947006, 65.30579256, 67.04211506,
        68.77843757, 70.51476007, 72.25108257, 73.98740508, 75.72372758,
        77.46005008, 79.19637259, 80.93269509, 82.66901759, 84.40534009,
        86.1416626 ]),
 <a list of 50 Patch objects>)
```




```
In [31]: plt.hist(y, bins = 50)

Out[31]: (array([1.182e+03, 2.820e+02, 1.730e+02, 1.110e+02, 7.400e+01, 7.100e+01,
                 6.000e+01, 4.100e+01, 3.700e+01, 2.800e+01, 4.000e+01, 3.300e+01,
                 2.100e+01, 2.400e+01, 3.100e+01, 1.700e+01, 2.100e+01, 2.600e+01,
                 1.800e+01, 1.900e+01, 1.700e+01, 1.300e+01, 1.900e+01, 7.000e+00,
                 1.800e+01, 1.000e+01, 8.000e+00, 9.000e+00, 1.200e+01, 5.000e+00,
                 8.000e+00, 2.000e+00, 9.000e+00, 6.000e+00, 6.000e+00, 3.000e+00,
                 6.000e+00, 2.000e+00, 2.000e+00, 1.000e+00, 4.000e+00, 7.000e+00,
                 2.000e+00, 2.000e+00, 2.000e+00, 0.000e+00, 1.000e+00, 1.000e+00,
                 1.000e+00, 1.000e+00]),
          array([ 0.   ,  1.719,  3.438,  5.157,  6.876,  8.595, 10.314, 12.033,
```

```
       13.752, 15.471, 17.19 , 18.909, 20.628, 22.347, 24.066, 25.785,
       27.504, 29.223, 30.942, 32.661, 34.38 , 36.099, 37.818, 39.537,
       41.256, 42.975, 44.694, 46.413, 48.132, 49.851, 51.57 , 53.289,
       55.008, 56.727, 58.446, 60.165, 61.884, 63.603, 65.322, 67.041,
       68.76 , 70.479, 72.198, 73.917, 75.636, 77.355, 79.074, 80.793,
       82.512, 84.231, 85.95 ]),
<a list of 50 Patch objects>)
```



In [32]:
```
y_pred.size
```

Out[32]:
```
2493
```

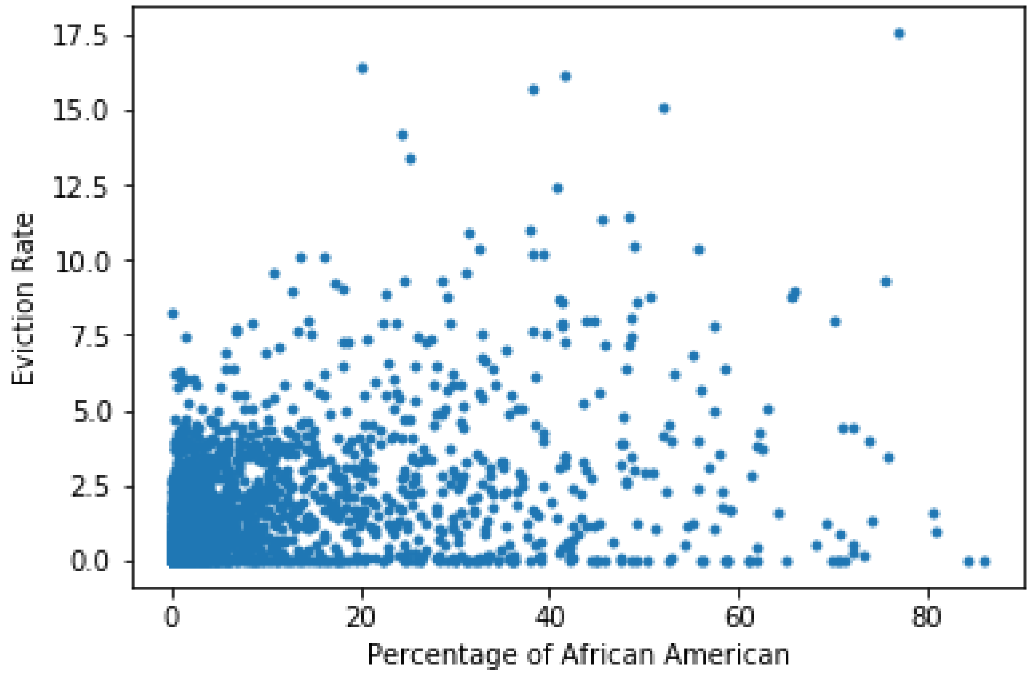
In [33]:
```
#bukets width = 5
df_y_pred = pd.DataFrame(y_pred, columns = {'y_pred'})
```

In [34]:
```
df_16.reset_index(drop = True, inplace = True)
```

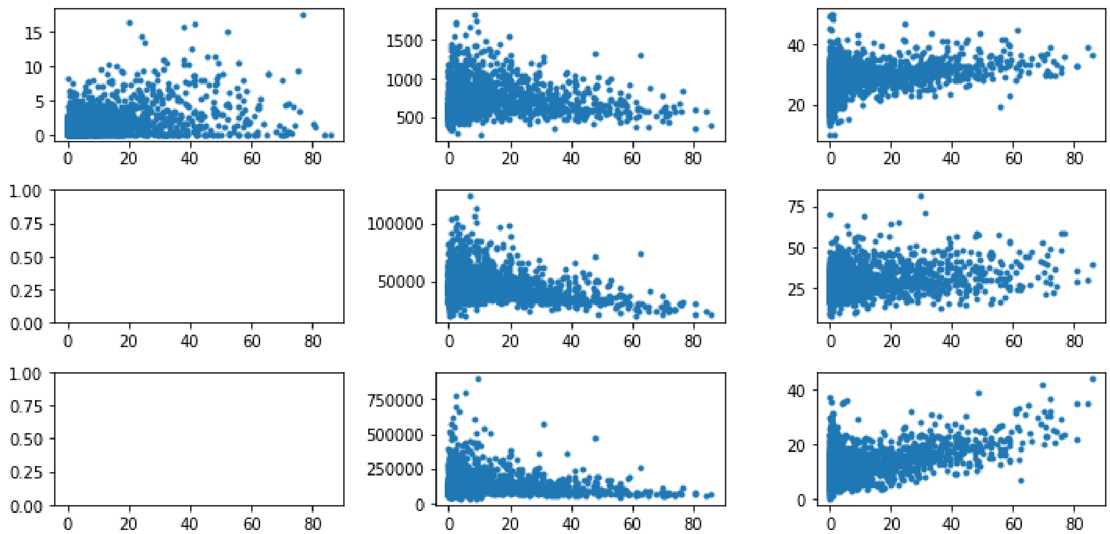
In [35]:
```
df_p = pd.concat([df_16, df_y_pred], axis = 1)
```

In [36]:
```
plt.plot(df_p.pct_af_am, df_p.eviction_rate,'.')
plt.xlabel('Percentage of African American')
plt.ylabel('Eviction Rate')
np.corrcoef(df_p.pct_af_am, df_p.eviction_rate)
```

Out[36]:
```
array([[1.        , 0.37540872],
       [0.37540872, 1.        ]])
```




```
In [58]: fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
         ax1.plot(df_16.pct_af_am, df_16.eviction_rate,'.')

         ax2.plot(df_16.pct_af_am, df_16.median_gross_rent, '.')
         ax3.plot(df_16.pct_af_am, df_16.rent_burden, '.')
         ax5.plot(df_16.pct_af_am, df_16.median_household_income, '.')

         ax6.plot(df_16.pct_af_am, df_16.pct_renter_occupied, '.')
         ax8.plot(df_16.pct_af_am, df_16.median_property_value, '.')
         ax9.plot(df_16.pct_af_am, df_16.poverty_rate, '.')

         plt.tight_layout()
```




```
In [38]: np.corrcoef([df_16.pct_af_am, df_16.eviction_rate,df_16.median_gross_rent, df_16.rent_
                      df_16.median_household_income, df_16.pct_renter_occupied, df_16.median_pr
                      df_16.poverty_rate])[0]
```

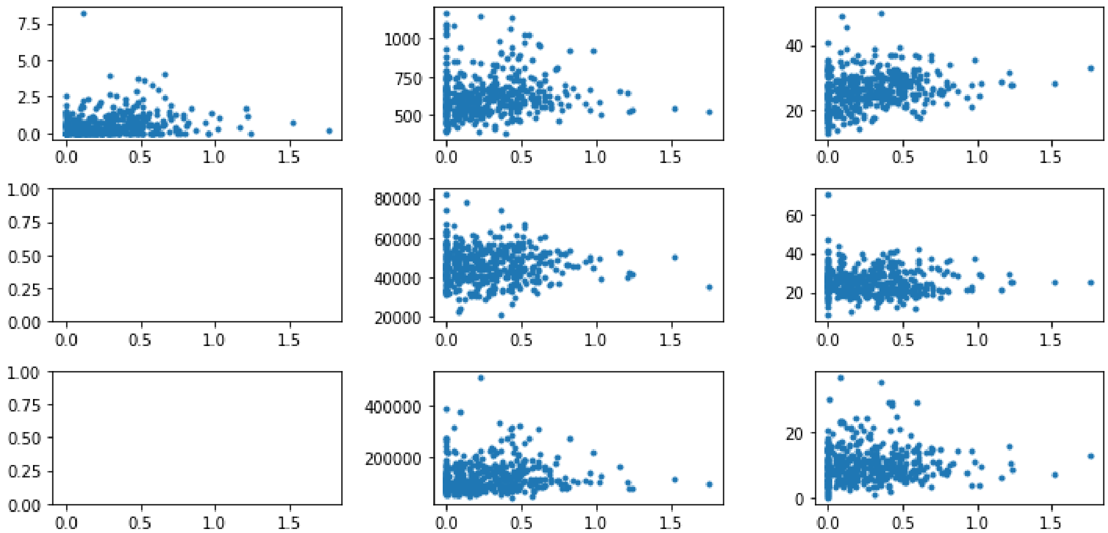
```
Out[38]: array([ 1.        ,  0.37540872,  0.04596906,  0.35152739, -0.25884827,
                 0.30675884, -0.08630837,  0.50951121])
```

2 correlation of pct_af_am and eviction rates within buckets

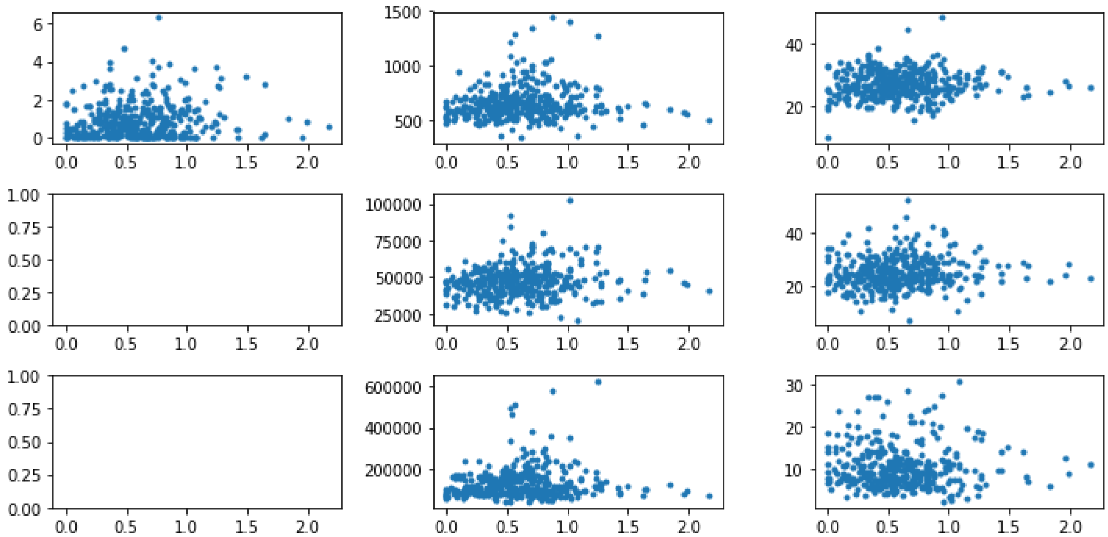
2.1 bucket of predicted pct_af_am of < 1% has high correlation

```
In [68]: df_10 = df_p[(df_p.y_pred <= 0.5)]

         fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
         ax1.plot(df_10.pct_af_am, df_10.eviction_rate,'.')

         ax2.plot(df_10.pct_af_am, df_10.median_gross_rent, '.')
         ax3.plot(df_10.pct_af_am, df_10.rent_burden, '.')
         ax5.plot(df_10.pct_af_am, df_10.median_household_income, '.')

         ax6.plot(df_10.pct_af_am, df_10.pct_renter_occupied, '.')
         ax8.plot(df_10.pct_af_am, df_10.median_property_value, '.')
         ax9.plot(df_10.pct_af_am, df_10.poverty_rate, '.')

         plt.tight_layout()

         np.corrcoef([df_10.pct_af_am, df_10.eviction_rate,df_10.median_gross_rent, df_10.rent_
                      df_10.median_household_income, df_10.pct_renter_occupied, df_10.median_pr
                      df_10.poverty_rate])[0]
```

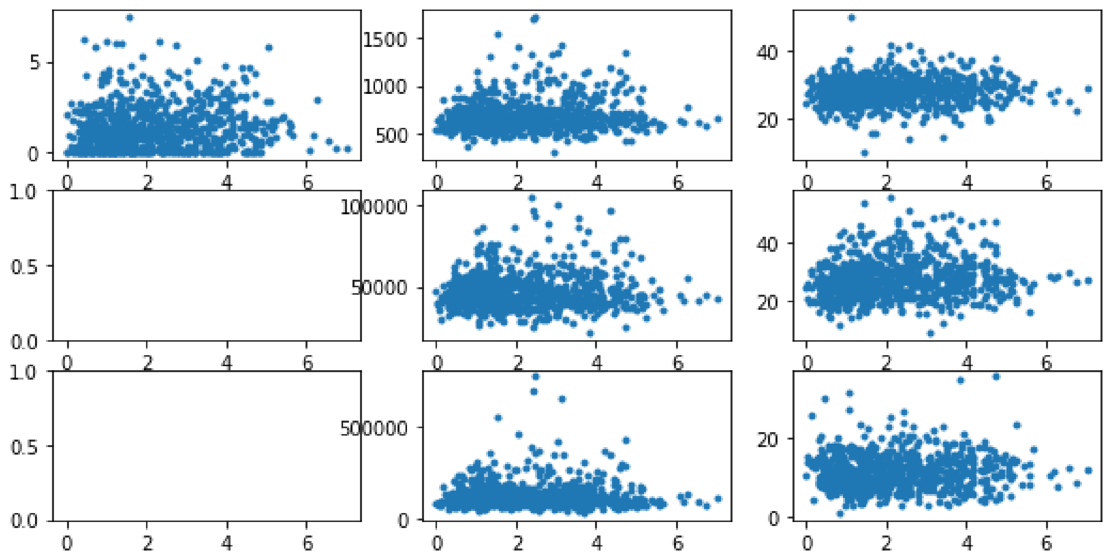
```
Out[68]: array([ 1.        ,  0.1824601 ,  0.05595222,  0.22007686,  0.01171619,
               -0.02543839,  0.07488983,  0.00872129])
```



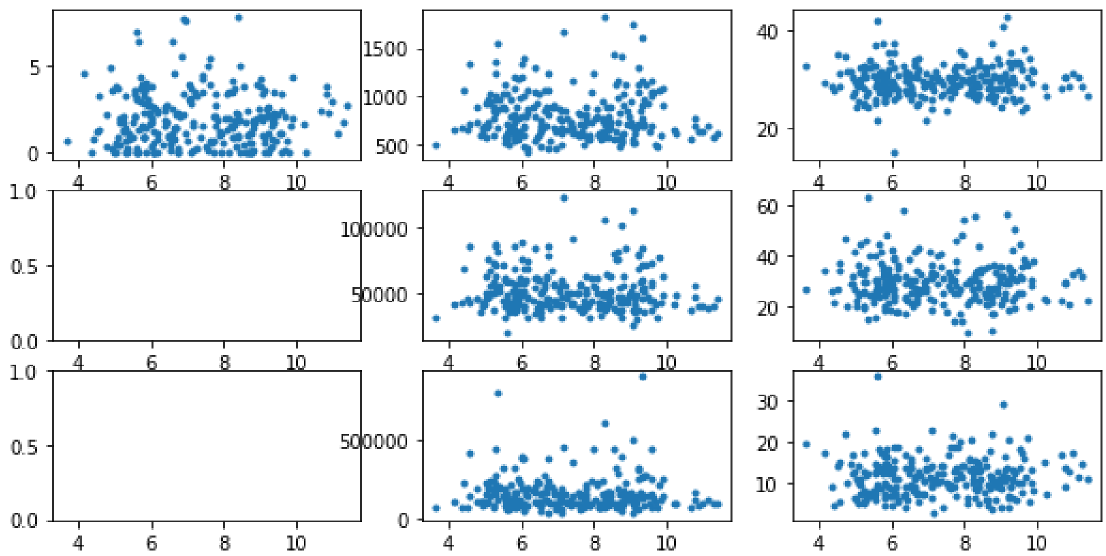

```
In [62]: df_10 = df_p[(df_p.y_pred > .5) & (df_p.y_pred <= 1)]

         fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
         ax1.plot(df_10.pct_af_am, df_10.eviction_rate,'.')

         ax2.plot(df_10.pct_af_am, df_10.median_gross_rent, '.')
         ax3.plot(df_10.pct_af_am, df_10.rent_burden, '.')
         ax5.plot(df_10.pct_af_am, df_10.median_household_income, '.')

         ax6.plot(df_10.pct_af_am, df_10.pct_renter_occupied, '.')
         ax8.plot(df_10.pct_af_am, df_10.median_property_value, '.')
         ax9.plot(df_10.pct_af_am, df_10.poverty_rate, '.')

         plt.tight_layout()

         np.corrcoef([df_10.pct_af_am, df_10.eviction_rate,df_10.median_gross_rent, df_10.rent_
                      df_10.median_household_income, df_10.pct_renter_occupied, df_10.median_p
                      df_10.poverty_rate])[0]

Out[62]: array([ 1.        ,  0.11146696,  0.09238938,  0.04932082,  0.09399575,
                0.09348859,  0.08892346, -0.0212685 ])
```



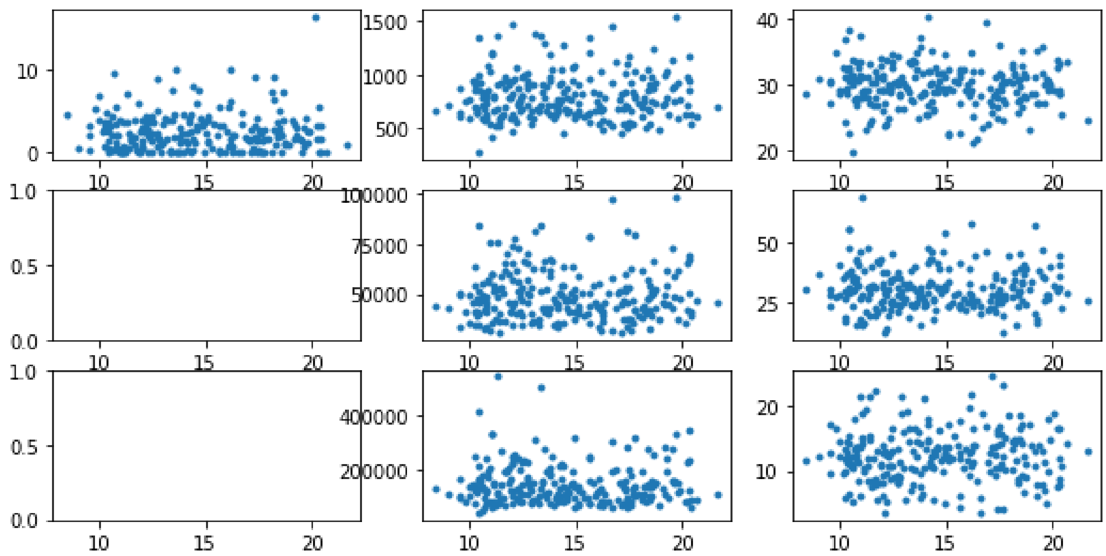
```
In [53]: df_10 = df_p[(df_p.y_pred > 1) & (df_p.y_pred <= 5)]

         fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
         ax1.plot(df_10.pct_af_am, df_10.eviction_rate,'.')

         ax2.plot(df_10.pct_af_am, df_10.median_gross_rent, '.')
         ax3.plot(df_10.pct_af_am, df_10.rent_burden, '.')
         ax5.plot(df_10.pct_af_am, df_10.median_household_income, '.')

         ax6.plot(df_10.pct_af_am, df_10.pct_renter_occupied, '.')
         ax8.plot(df_10.pct_af_am, df_10.median_property_value, '.')
         ax9.plot(df_10.pct_af_am, df_10.poverty_rate, '.')


         np.corrcoef([df_10.pct_af_am, df_10.eviction_rate,df_10.median_gross_rent, df_10.rent_
                      df_10.median_household_income, df_10.pct_renter_occupied, df_10.median_p
                      df_10.poverty_rate])[0]

Out[53]: array([1.        , 0.0714252 , 0.11528813, 0.07601134, 0.03638695,
                0.12387165, 0.03845003, 0.04877244])
```




```
In [45]: df_10 = df_p[(df_p.y_pred > 5) & (df_p.y_pred <= 10)]

         fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
         ax1.plot(df_10.pct_af_am, df_10.eviction_rate,'.')

         ax2.plot(df_10.pct_af_am, df_10.median_gross_rent, '.')
         ax3.plot(df_10.pct_af_am, df_10.rent_burden, '.')
         ax5.plot(df_10.pct_af_am, df_10.median_household_income, '.')

         ax6.plot(df_10.pct_af_am, df_10.pct_renter_occupied, '.')
         ax8.plot(df_10.pct_af_am, df_10.median_property_value, '.')
         ax9.plot(df_10.pct_af_am, df_10.poverty_rate, '.')


         np.corrcoef([df_10.pct_af_am, df_10.eviction_rate,df_10.median_gross_rent, df_10.rent_
                      df_10.median_household_income, df_10.pct_renter_occupied, df_10.median_p
                      df_10.poverty_rate])[0]

Out[45]: array([ 1.        , -0.01217197, -0.00617623,  0.04694456, -0.019619  ,
                -0.01746704, -0.00518995,  0.02837812])
```

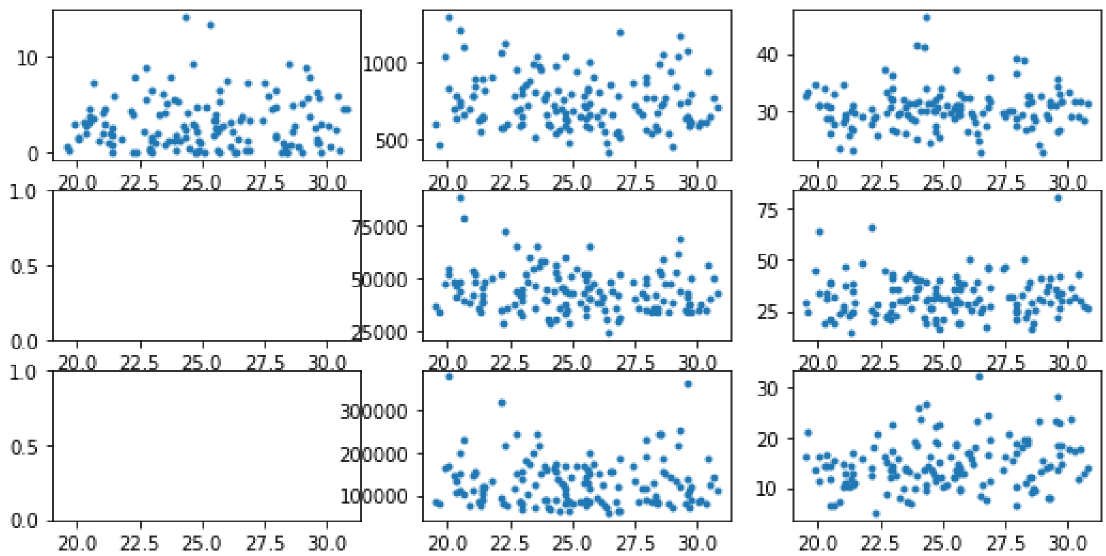


```
In [46]: df_10 = df_p[(df_p.y_pred > 10) & (df_p.y_pred <= 20)]
         fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
         ax1.plot(df_10.pct_af_am, df_10.eviction_rate,'.')

         ax2.plot(df_10.pct_af_am, df_10.median_gross_rent, '.')
         ax3.plot(df_10.pct_af_am, df_10.rent_burden, '.')
         ax5.plot(df_10.pct_af_am, df_10.median_household_income, '.')

         ax6.plot(df_10.pct_af_am, df_10.pct_renter_occupied, '.')
         ax8.plot(df_10.pct_af_am, df_10.median_property_value, '.')
         ax9.plot(df_10.pct_af_am, df_10.poverty_rate, '.')

         np.corrcoef([df_10.pct_af_am, df_10.eviction_rate,df_10.median_gross_rent, df_10.rent_
                      df_10.median_household_income, df_10.pct_renter_occupied, df_10.median_p
                      df_10.poverty_rate])[0]

Out[46]: array([ 1.        ,  0.03173978,  0.02017166, -0.04383174,  0.01557254,
                -0.02629626, -0.02995587,  0.04468589])
```




```
In [47]: df_10 = df_p[(df_p.y_pred > 20) & (df_p.y_pred <= 30)]

         fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
         ax1.plot(df_10.pct_af_am, df_10.eviction_rate,'.')

         ax2.plot(df_10.pct_af_am, df_10.median_gross_rent, '.')
         ax3.plot(df_10.pct_af_am, df_10.rent_burden, '.')
         ax5.plot(df_10.pct_af_am, df_10.median_household_income, '.')

         ax6.plot(df_10.pct_af_am, df_10.pct_renter_occupied, '.')
         ax8.plot(df_10.pct_af_am, df_10.median_property_value, '.')
         ax9.plot(df_10.pct_af_am, df_10.poverty_rate, '.')

         np.corrcoef([df_10.pct_af_am, df_10.eviction_rate,df_10.median_gross_rent, df_10.rent_
                      df_10.median_household_income, df_10.pct_renter_occupied, df_10.median_p
                      df_10.poverty_rate])[0]
```

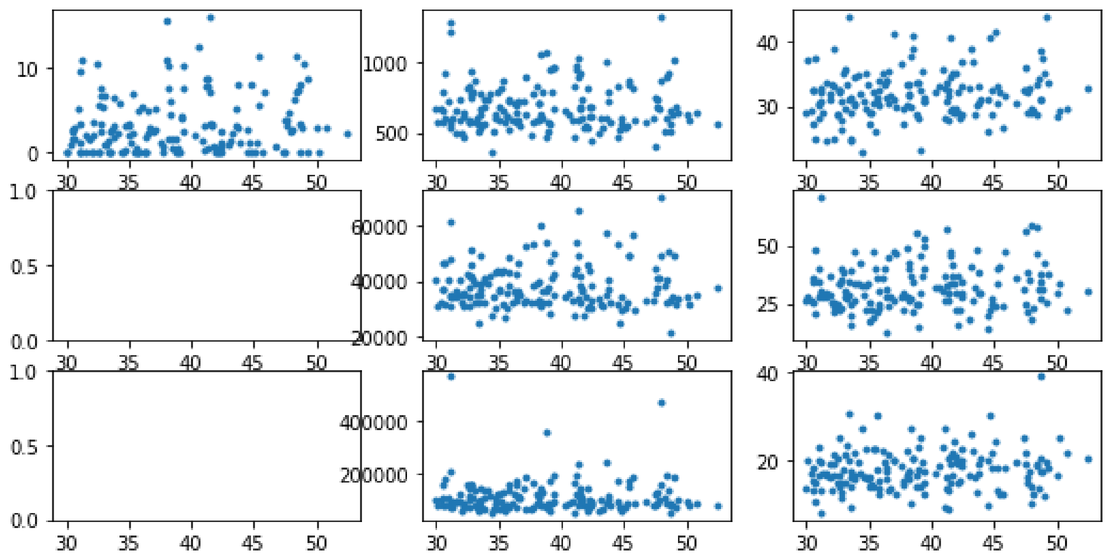
```
Out[47]: array([ 1.        ,  0.05308549, -0.11344714,  0.03339661, -0.15610378,
                0.05260499, -0.04112884,  0.19882068])
```



3 bucket of predicted pct_af_am of (30, 40] has high correlation

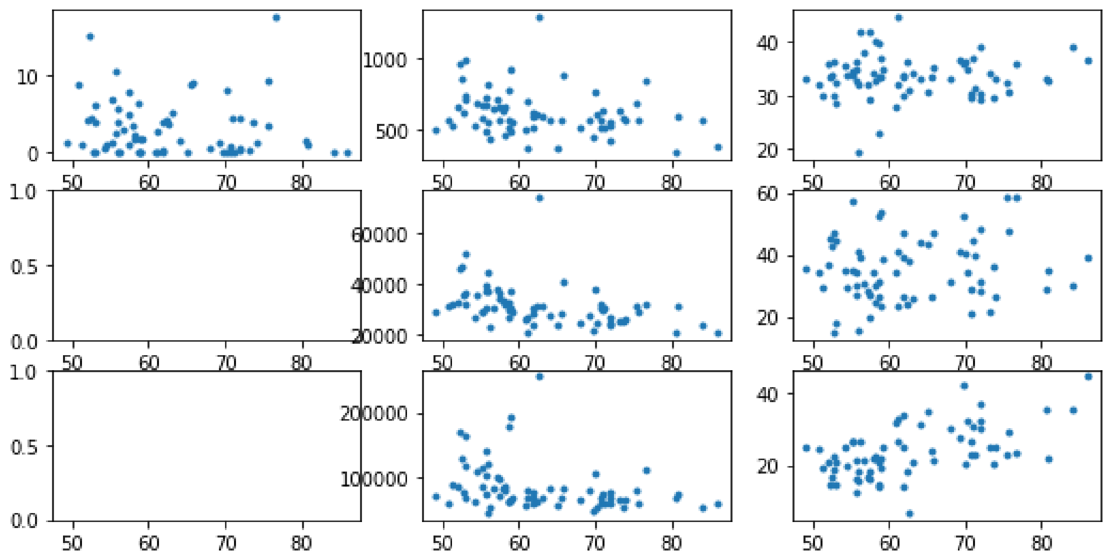
In [63]:
```
df_10 = df_p[(df_p.y_pred > 30) & (df_p.y_pred <= 50)]

fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
ax1.plot(df_10.pct_af_am, df_10.eviction_rate,'.')

ax2.plot(df_10.pct_af_am, df_10.median_gross_rent, '.')
ax3.plot(df_10.pct_af_am, df_10.rent_burden, '.')
ax5.plot(df_10.pct_af_am, df_10.median_household_income, '.')

ax6.plot(df_10.pct_af_am, df_10.pct_renter_occupied, '.')
ax8.plot(df_10.pct_af_am, df_10.median_property_value, '.')
ax9.plot(df_10.pct_af_am, df_10.poverty_rate, '.')

np.corrcoef([df_10.pct_af_am, df_10.eviction_rate,df_10.median_gross_rent, df_10.rent_
             df_10.median_household_income, df_10.pct_renter_occupied, df_10.median_p
             df_10.poverty_rate])[0]
```

Out[63]:
```
array([ 1.        ,  0.13832433,  0.01854265,  0.13618926,  0.01891658,
        0.09869172, -0.0033383 ,  0.12573548])
```



```
In [65]: df_10 = df_p[(df_p.y_pred > 50)]
         fig, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9)) = plt.subplots(3,3, figsize=
         ax1.plot(df_10.pct_af_am, df_10.eviction_rate,'.')

         ax2.plot(df_10.pct_af_am, df_10.median_gross_rent, '.')
         ax3.plot(df_10.pct_af_am, df_10.rent_burden, '.')
         ax5.plot(df_10.pct_af_am, df_10.median_household_income, '.')

         ax6.plot(df_10.pct_af_am, df_10.pct_renter_occupied, '.')
         ax8.plot(df_10.pct_af_am, df_10.median_property_value, '.')
         ax9.plot(df_10.pct_af_am, df_10.poverty_rate, '.')

         np.corrcoef([df_10.pct_af_am, df_10.eviction_rate,df_10.median_gross_rent, df_10.rent_
                      df_10.median_household_income, df_10.pct_renter_occupied, df_10.median_p
                      df_10.poverty_rate])[0]
```

```
Out[65]: array([ 1.        , -0.08577344, -0.26284113,  0.05793828, -0.38960917,
                 0.14917251, -0.3067337 ,  0.55457192])
```



10
0
1000
500
40
30
20
1.0
0.5
0.0
60000
40000
20000
60
40
20
200000
100000
50
60
70
80