In [74]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

School district suspensions data come from the US Dept of Education Office of Civil Rights Data Collection

[https://ocrdata.ed.gov/Home (https://ocrdata.ed.gov/Home)](https://ocrdata.ed.gov/Home)

Load States Suspenions Data

In [75]:

```
from os import listdir

susp = listdir('suspensions/states')

# oss = out-of-school suspension
oss = pd.concat([pd.read_csv('suspensions/states/' + state) for state in susp]).reset_index(drop=True)

oss = oss.drop(columns=['SWD (IDEA-Eligible)', 'SWD (Section 504 only)', 'LEP'])

# Need to add 0's for district ID's with only 6 digits
oss['ID'] = oss['ID'].astype(str)
oss['ID'] = ['0' + row if len(row) < 7 else row for row in oss['ID']]

oss.loc[oss['Category'] == 'School days missed due to out-of-school suspension', 'Category'] = 'Suspensions'

oss.head(10)
```

Out[75]:

	Lea State	LEA	ID	Year	Category	Sex	American Indian or Alaska Native	Asian	Hawaiian/ Pacific Islander	Hispanic	Black	White	Two or more races	Total
0	AK	Craig City School District	0200090	2015	Suspensions	M	7.0	0.0	0.0	0.0	0.0	11.0	0.0	18.0
1	AK	Craig City School District	0200090	2015	Suspensions	F	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
2	AK	Craig City School District	0200090	2015	Total enrollment	M	59.0	7.0	0.0	5.0	0.0	185.0	36.0	292.0
3	AK	Craig City School District	0200090	2015	Total enrollment	F	56.0	12.0	2.0	5.0	2.0	167.0	26.0	270.0
4	AK	Sitka School District	0200240	2015	Suspensions	M	18.0	0.0	0.0	0.0	0.0	19.0	0.0	37.0
5	AK	Sitka School District	0200240	2015	Suspensions	F	23.0	0.0	0.0	0.0	0.0	10.0	0.0	33.0
6	AK	Sitka School District	0200240	2015	Total enrollment	M	213.0	76.0	8.0	37.0	11.0	375.0	32.0	752.0
7	AK	Sitka School District	0200240	2015	Total enrollment	F	189.0	49.0	9.0	19.0	10.0	315.0	32.0	623.0

	Lea State	LEA	ID	Year	Category	Sex	American Indian or Alaska Native	Asian	Hawaiian/ Pacific Islander	Hispanic	Black	White	Two or more races	Total
8	AK	Bering Strait School District	0200020	2015	Suspensions	M	327.0	0.0	0.0	0.0	0.0	0.0	0.0	327.0
9	AK	Bering Strait School District	0200020	2015	Suspensions	F	150.0	0.0	0.0	0.0	0.0	0.0	0.0	150.0

In [76]:

```
# Load geographic data from Common Core data file
counties = pd.read_csv('suspensions/counties/district_geo_data.csv', encoding='latin-1')

# Need to fix LEAID's that are missing 0's to match with suspension data
counties['LEAID'] = counties['LEAID'].astype(str)
counties['LEAID'] = ['0' + row if len(row) < 7 else row for row in counties['LEAID']]
counties.head()
```

Out[76]:

	SURVYEAR	LEAID	FIPST	LSTREE	LCITY	LSTATE	LZIP	LZIP4	LATCODE	LONGCODE	CONUM	CONAME	CD
0	2014	0100002	1	1000 INDUSTRIAL SCHOOL ROAD	MT. MEIGS	AL	36057	66.0	33.673661	-86.628755	1073	JEFFERSON COUNTY	106
1	2014	0100005	1	107 WEST MAIN STREET	ALBERTVILLE	AL	35950	25.0	34.267500	-86.208600	1095	MARSHALL COUNTY	104
2	2014	0100006	1	12380 US HIGHWAY 431 S	GUNTERSVILLE	AL	35976	9351.0	34.304968	-86.286673	1095	MARSHALL COUNTY	104
3	2014	0100007	1	2810 METROPOLITAN WAY	HOOVER	AL	35243	5500.0	33.406200	-86.766900	1073	JEFFERSON COUNTY	106
4	2014	0100008	1	211 CELTIC DRIVE	MADISON	AL	35758	1615.0	34.687312	-86.744874	1089	MADISON COUNTY	105

Merge district geographic data with suspension data

In [77]:

```python
susp = oss.merge(counties, left_on='ID', right_on='LEAID', copy=False)

drops = ['SURVYEAR', 'FIPST', 'LEAID', 'LSTATE', 'LSTREE', 'LZIP', 'LZIP4', 'LATCODE', 'LONGCODE',
         'CD', 'LOCALE', 'CBSA', 'CSA', 'NECTA', 'METMIC']

susp = susp.drop(columns=drops)

# Append state abbreviations to city and county names
# to avoid grouping together cities/counties with same names from different states
susp['LCITY'] = susp['LCITY'] + ', ' + susp['Lea State']
susp['CONAME'] = susp['CONAME'] + ', ' + susp['Lea State']
susp.head()
```

Out[77]:

	Lea State	LEA	ID	Year	Category	Sex	American Indian or Alaska Native	Asian	Hawaiian/ Pacific Islander	Hispanic	Black	White	Two or more races	Total	LCITY	CONUM	CON
0	AK	Craig City School District	0200090	2015	Suspensions	M	7.0	0.0	0.0	0.0	0.0	11.0	0.0	18.0	CRAIG, AK	2198	PRINC WA HY CEI ARE
1	AK	Craig City School District	0200090	2015	Suspensions	F	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	CRAIG, AK	2198	PRINC WA HY CEI ARE
2	AK	Craig City School District	0200090	2015	Total enrollment	M	59.0	7.0	0.0	5.0	0.0	185.0	36.0	292.0	CRAIG, AK	2198	PRINC WA HY CEI ARE
3	AK	Craig City School District	0200090	2015	Total enrollment	F	56.0	12.0	2.0	5.0	2.0	167.0	26.0	270.0	CRAIG, AK	2198	PRINC WA HY CEI ARE
4	AK	Sitka School District	0200240	2015	Suspensions	M	18.0	0.0	0.0	0.0	0.0	19.0	0.0	37.0	SITKA, AK	2220	SITKA BORO

Calculate the suspension rate (suspension days/enrollment) by gender, average by county

In [78]:

```python
demog = ['American Indian or Alaska Native', 'Asian', 'Hawaiian/ Pacific Islander', 'Hispanic', 'Black',
         'White', 'Two or more races', 'Total']

def sex(df, s):
    return df[df['Sex'] == s].reset_index(drop=True)

male = sex(susp, 'M')
female = sex(susp, 'F')

male[demog] = male[demog] + female[demog]

tot = male.drop(columns=['Sex'])

def sep_cats(df, catg):
    return df[df['Category'] == catg].reset_index(drop=True)

tot_sus = sep_cats(tot, 'Suspensions')
tot_enr = sep_cats(tot, 'Total enrollment')

tot = tot_sus.join(tot_enr[demog], lsuffix='_suspensions', rsuffix='_enrollment')

tot = tot[['CONAME', 'American Indian or Alaska Native_suspensions', 'American Indian or Alaska Native_enrollment',
           'Asian_suspensions', 'Asian_enrollment', 'Hawaiian/ Pacific Islander_suspensions',
           'Hawaiian/ Pacific Islander_enrollment', 'Hispanic_suspensions', 'Hispanic_enrollment',
           'Black_suspensions', 'Black_enrollment', 'White_suspensions', 'White_enrollment',
           'Two or more races_suspensions', 'Two or more races_enrollment', 'Total_suspensions',
           'Total_enrollment']]


def susp_rate(df):
    for race in demog:
        df[race + '_suspension rate'] = df[race + '_suspensions'] / df[race + '_enrollment']
    return df.fillna(0)

tot_rates = susp_rate(tot)

tot_rates = tot_rates[['CONAME', 'Total_suspensions', 'Total_enrollment', 'Total_suspension rate',
                       'American Indian or Alaska Native_suspensions','American Indian or Alaska Native_enrollment',
                       'American Indian or Alaska Native_suspension rate', 'Asian_suspensions', 'Asian_enrollment',
                       'Asian_suspension rate', 'Hawaiian/ Pacific Islander_suspensions',
                       'Hawaiian/ Pacific Islander_enrollment', 'Hawaiian/ Pacific Islander_suspension rate',
```

```
                      'Hispanic_suspensions', 'Hispanic_enrollment', 'Hispanic_suspension rate', 'Black_suspensions'
                      'Black_enrollment', 'Black_suspension rate', 'White_suspensions', 'White_enrollment',
                      'White_suspension rate', 'Two or more races_suspensions', 'Two or more races_enrollment',
                      'Two or more races_suspension rate']]

county_rates = tot_rates.groupby('CONAME').mean().reset_index()
county_rates.head()
```

Out[78]:

	CONAME	Total_suspensions	Total_enrollment	Total_suspension rate	American Indian or Alaska Native_suspensions	American Indian or Alaska Native_enrollment	American Indian or Alaska Native_suspension rate	Asian_suspen
0	ABBEVILLE COUNTY, SC	412.00	3038.0	0.135616	0.00	8.00	0.00000	
1	ACADIA PARISH, LA	6563.00	10111.0	0.649095	0.00	33.00	0.00000	
2	ACCOMACK COUNTY, VA	1724.00	5369.0	0.321103	0.00	13.00	0.00000	
3	ADA COUNTY, ID	750.75	17359.0	0.035898	5.75	109.25	0.03321	
4	ADAIR COUNTY, IA	12.50	435.5	0.024276	0.00	3.00	0.00000	

5 rows × 25 columns

Load evictions data for counties

Data come from the Eviction Lab at Princeton, the first comprehensive national database of court evictions data

[https://evictionlab.org/ (https://evictionlab.org/)](https://evictionlab.org/)

Variable Descriptions:

-https://eviction-lab-data-downloads.s3.amazonaws.com/DATA_DICTIONARY.txt (https://eviction-lab-data-downloads.s3.amazonaws.com/DATA_DICTIONARY.txt)

In [79]:

```
counties = pd.read_csv('evictions/cities/USA_counties.csv').dropna()

counties = counties[counties['year'] == 2015]

state_abbrevs = {'Alabama': 'AL', 'Alaska': 'AK', 'American Samoa': 'AS', 'Arizona': 'AZ', 'Arkansas': 'AR',
                 'California': 'CA', 'Colorado': 'CO', 'Connecticut': 'CT', 'Delaware': 'DE',
                 'District of Columbia': 'DC', 'Florida': 'FL', 'Georgia': 'GA', 'Guam': 'GU', 'Hawaii': 'HI',
                 'Idaho': 'ID', 'Illinois': 'IL', 'Indiana': 'IN', 'Iowa': 'IA', 'Kansas': 'KS', 'Kentucky': 'KY',
                 'Louisiana': 'LA', 'Maine': 'ME', 'Maryland': 'MD', 'Massachusetts': 'MA', 'Michigan': 'MI',
                 'Minnesota': 'MN', 'Mississippi': 'MS', 'Missouri': 'MO', 'Montana': 'MT', 'Nebraska': 'NE',
                 'Nevada': 'NV', 'New Hampshire': 'NH', 'New Jersey': 'NJ', 'New Mexico': 'NM', 'New York': 'NY',
                 'North Carolina': 'NC', 'North Dakota': 'ND', 'Northern Mariana Islands':'MP', 'Ohio': 'OH',
                 'Oklahoma': 'OK', 'Oregon': 'OR', 'Pennsylvania': 'PA', 'Puerto Rico': 'PR', 'Rhode Island': 'RI',
                 'South Carolina': 'SC', 'South Dakota': 'SD', 'Tennessee': 'TN', 'Texas': 'TX', 'Utah': 'UT',
                 'Vermont': 'VT', 'Virgin Islands': 'VI', 'Virginia': 'VA', 'Washington': 'WA', 'West Virginia': 'WV
                 'Wisconsin': 'WI', 'Wyoming': 'WY'}

# All caps to match the county school district data
counties['parent-location'] = [state_abbrevs.get(row) for row in counties['parent-location']]
counties['name'] = counties['name'].str.upper() + ', ' + counties['parent-location'].str.upper()

counties.head()
```

Out[79]:

	GEOID	year	name	parent-location	population	poverty-rate	renter-occupied-households	pct-renter-occupied	median-gross-rent	median-household-income	...	pct-nh-pi	pct-multiple	pct-other	evictior filing
15	1001	2015	AUTAUGA COUNTY, AL	AL	55221.0	9.28	5307.0	26.08	883.0	51281.0	...	0.01	1.53	0.14	147.
32	1003	2015	BALDWIN COUNTY, AL	AL	195121.0	9.63	23302.0	28.48	879.0	50254.0	...	0.00	1.58	0.10	649.
49	1005	2015	BARBOUR COUNTY, AL	AL	26932.0	19.54	3327.0	36.41	579.0	32964.0	...	0.00	1.31	0.50	28.
66	1007	2015	BIBB COUNTY, AL	AL	22604.0	12.84	2077.0	24.89	651.0	38678.0	...	0.00	1.37	0.00	43.

	GEOID	year	name	parent-location	population	poverty-rate	renter-occupied-households	pct-renter-occupied	median-gross-rent	median-household-income	...	pct-nh-pi	pct-multiple	pct-other	evictior filing
83	1009	2015	BLOUNT COUNTY, AL	AL	57710.0	12.26	4498.0	21.10	601.0	45813.0	...	0.00	1.46	0.07	67.

5 rows × 27 columns

Merge county evictions data with suspension data

In [80]:

```
evct_susp = counties.merge(county_rates, left_on='name', right_on='CONAME', copy=False)

# Remove counties that reported no suspensions or evictions
def remove_zeros(df):
    df = df[(df['eviction-rate'] > 0) & (df['eviction-filing-rate'] > 0) & (df['Total_suspension rate'] > 0)]
    df = df.drop(columns=['low-flag', 'imputed', 'subbed', 'CONAME', 'parent-location', 'year', 'GEOID'])
    return df

evct_susp = remove_zeros(evct_susp)
evct_susp.describe()
```

Out[80]:

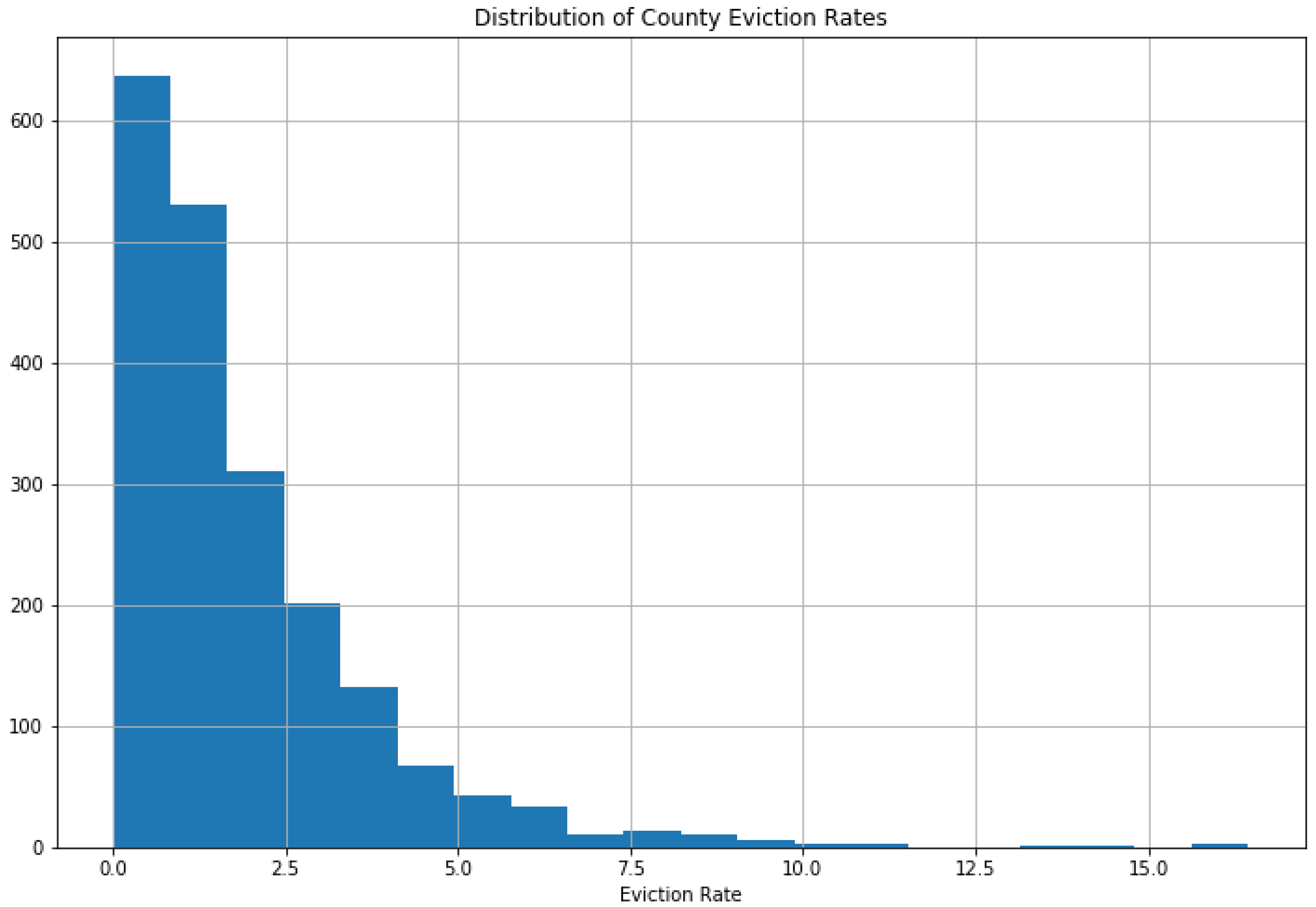
	population	poverty-rate	renter-occupied-households	pct-renter-occupied	median-gross-rent	median-household-income	median-property-value	rent-burden	pct-white	pct
count	2.005000e+03	2005.000000	2.005000e+03	2005.000000	2005.000000	2005.000000	2005.000000	2005.000000	2005.000000	2005.(
mean	1.247259e+05	12.035242	1.759729e+04	28.539845	714.936160	47173.483791	137643.441397	29.101297	78.872279	9.(
std	3.732031e+05	5.182603	6.300688e+04	7.725146	182.003166	11810.210648	74141.207206	3.853099	18.074770	13.8
min	1.862000e+03	2.580000	1.840000e+02	7.350000	343.000000	19328.000000	35500.000000	15.900000	7.280000	0.(
25%	1.644500e+04	8.230000	1.722000e+03	23.230000	595.000000	39459.000000	91700.000000	26.700000	68.490000	0.7
50%	3.426700e+04	11.290000	3.783000e+03	27.320000	669.000000	45644.000000	117700.000000	29.100000	85.200000	2.5
75%	8.690100e+04	14.690000	1.056800e+04	32.260000	786.000000	52374.000000	159700.000000	31.400000	93.420000	10.7
max	1.003839e+07	44.320000	1.776232e+06	70.730000	1827.000000	123453.000000	902500.000000	50.000000	99.500000	85.9

8 rows × 44 columns

Histogram showing distributions of county-level evictions

In [81]:

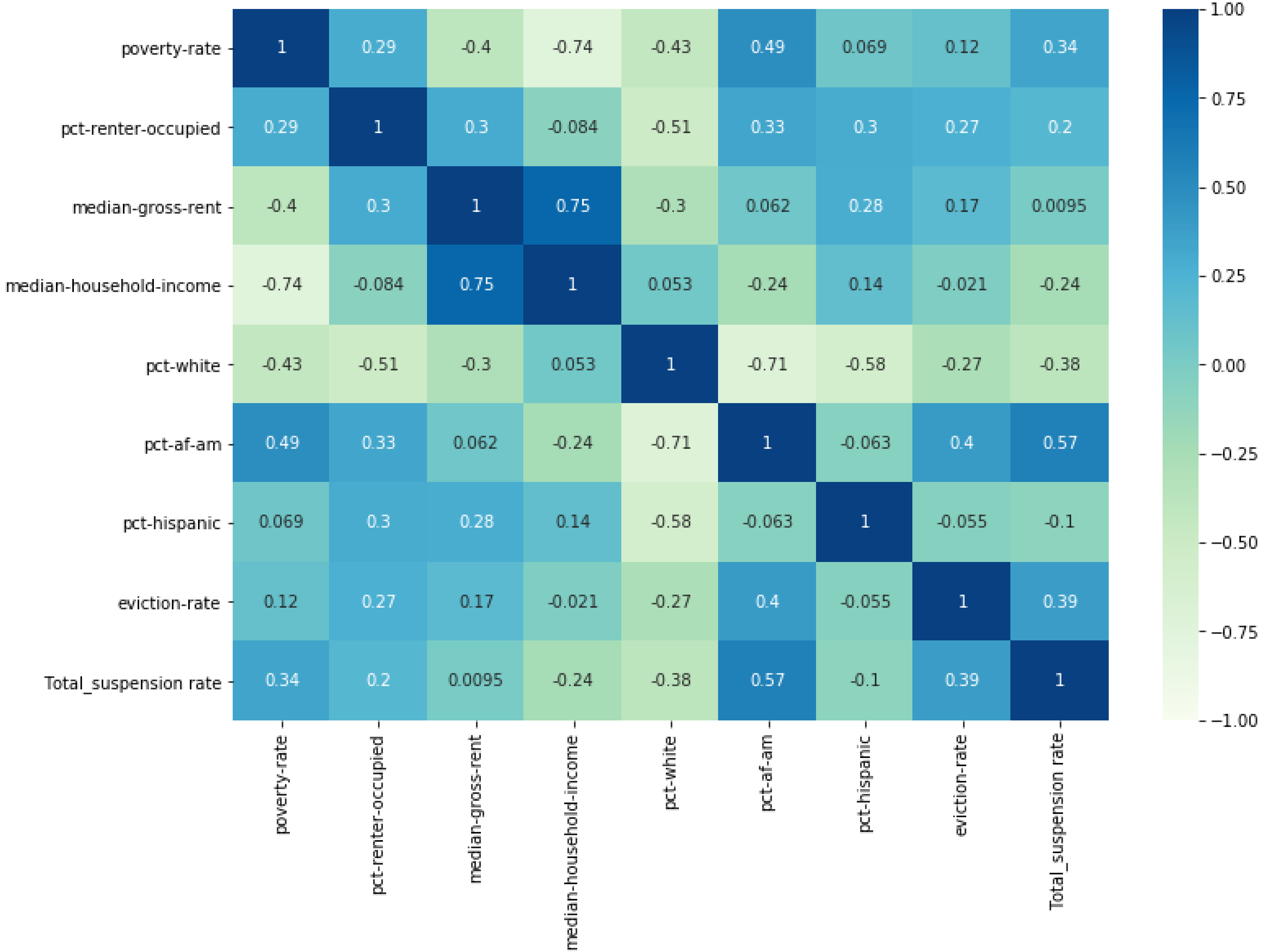
```
%matplotlib inline
plt.rcParams['figure.figsize'] = [12, 8]

x = evct_susp['eviction-rate']

plt.hist(x, bins=20)
plt.title('Distribution of County Eviction Rates')
plt.xlabel('Eviction Rate')
plt.grid()
plt.show()
```



Correlation matrix of demographics, evictions data, and suspensions data

In [82]:

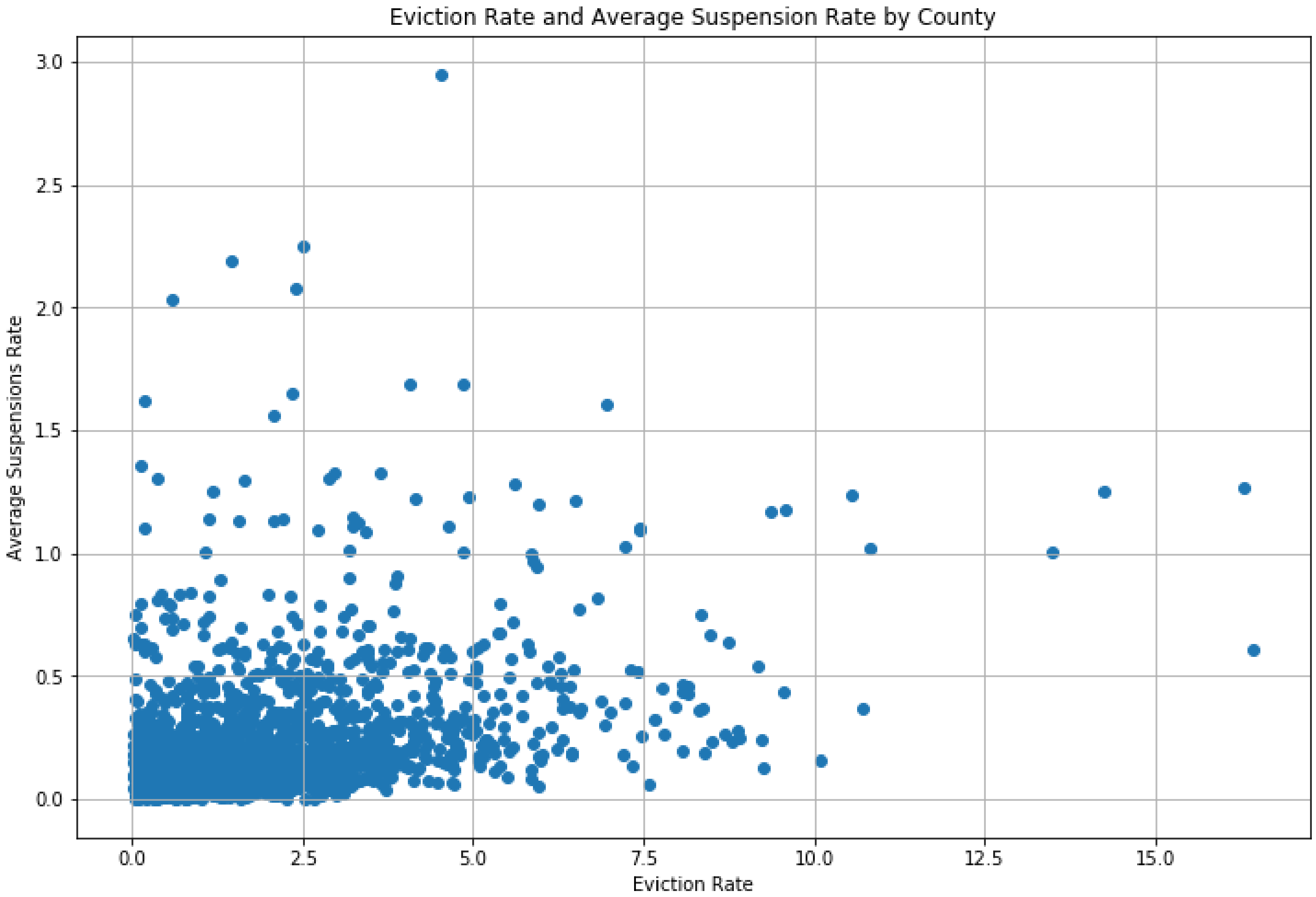
```
import seaborn as sns

corr = evct_susp[['poverty-rate', 'pct-renter-occupied', 'median-gross-rent', 'median-household-income',
                 'pct-white', 'pct-af-am', 'pct-hispanic', 'eviction-rate', 'Total_suspension rate']].corr()

ax = sns.heatmap(corr, vmin=-1, vmax=1, annot=True, cmap='GnBu')
```



Scatterplot for # evictions and # suspension days

In [83]:

```
X = evct_susp['eviction-rate']
y = evct_susp['Total_suspension rate']

plt.scatter(X, y)
plt.title('Eviction Rate and Average Suspension Rate by County')
plt.xlabel('Eviction Rate')
plt.ylabel('Average Suspensions Rate')
plt.grid()
plt.show()
```



There seems to be a positive, but not very strong relationship. There may be additional variables not included in the scatterplot that may be important.

In [84]:

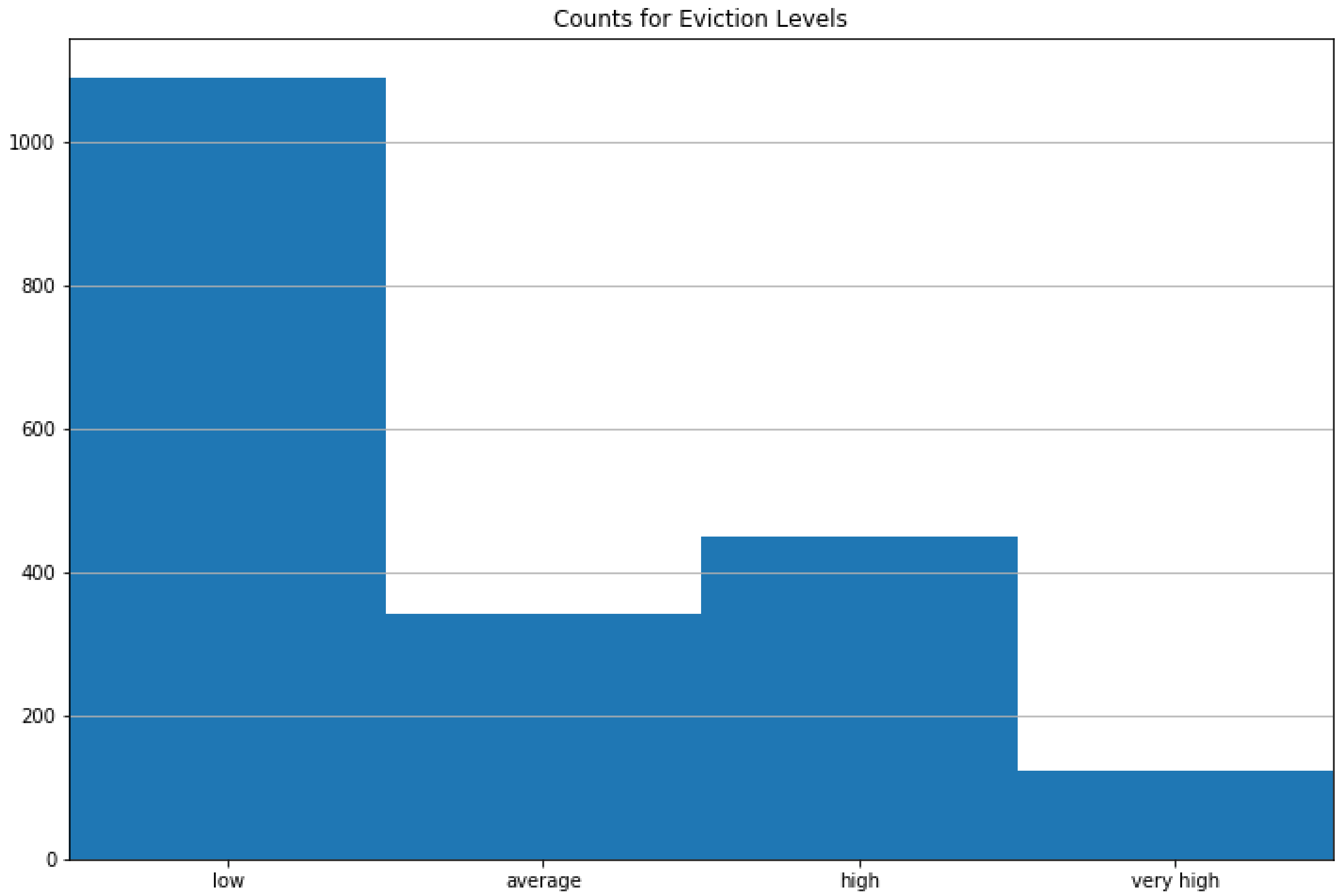
```
evct_susp[['eviction-rate']].describe()
```

Out[84]:

	eviction-rate
count	2005.000000
mean	1.893810
std	1.802584
min	0.010000
25%	0.660000
50%	1.360000
75%	2.560000
max	16.450000

In [85]:

```python
# Create eviction level column to categorize the data into low, average, and high

evct_susp['eviction level'] = pd.cut(evct_susp['eviction-rate'], bins=[0, 1.5, 2.35, 5, 17],
                                     labels=['low', 'average', 'high', 'very high'])

def bins_labels(bins):
    bin_w = (max(bins) - min(bins)) / (len(bins) - 1)
    plt.xticks(np.arange(min(bins)+bin_w/2, max(bins), bin_w), ['low', 'average', 'high', 'very high'])
    plt.xlim(bins[0], bins[-1])

bins = range(5)

plt.hist(evct_susp['eviction level'].sort_values(), bins=bins)
plt.title('Counts for Eviction Levels')
plt.grid(axis='y')
bins_labels(bins)
plt.show()
```


Counts for Eviction Levels
0
200
400
600
800
1000
low
average
high
very high

In [86]:
```
evct_susp[['Black_suspension rate', 'White_suspension rate', 'Total_suspension rate']].describe()
```

Out[86]:

	Black_suspension rate	White_suspension rate	Total_suspension rate
count	2005.000000	2005.000000	2005.000000
mean	0.370233	0.164138	0.214024
std	0.521843	0.198825	0.248975
min	0.000000	0.000000	0.000443
25%	0.045455	0.059533	0.067993
50%	0.246377	0.117037	0.140171
75%	0.513520	0.203519	0.262093
max	10.659091	3.814702	2.949467

In [87]:
```
evct_susp['suspension level'] = pd.cut(evct_susp['Total_suspension rate'], bins=[0, .05, .15, .25, 3],
                                        labels=['low', 'average', 'high', 'very high'])

evct_susp['suspension level'].value_counts().sort_index()
```

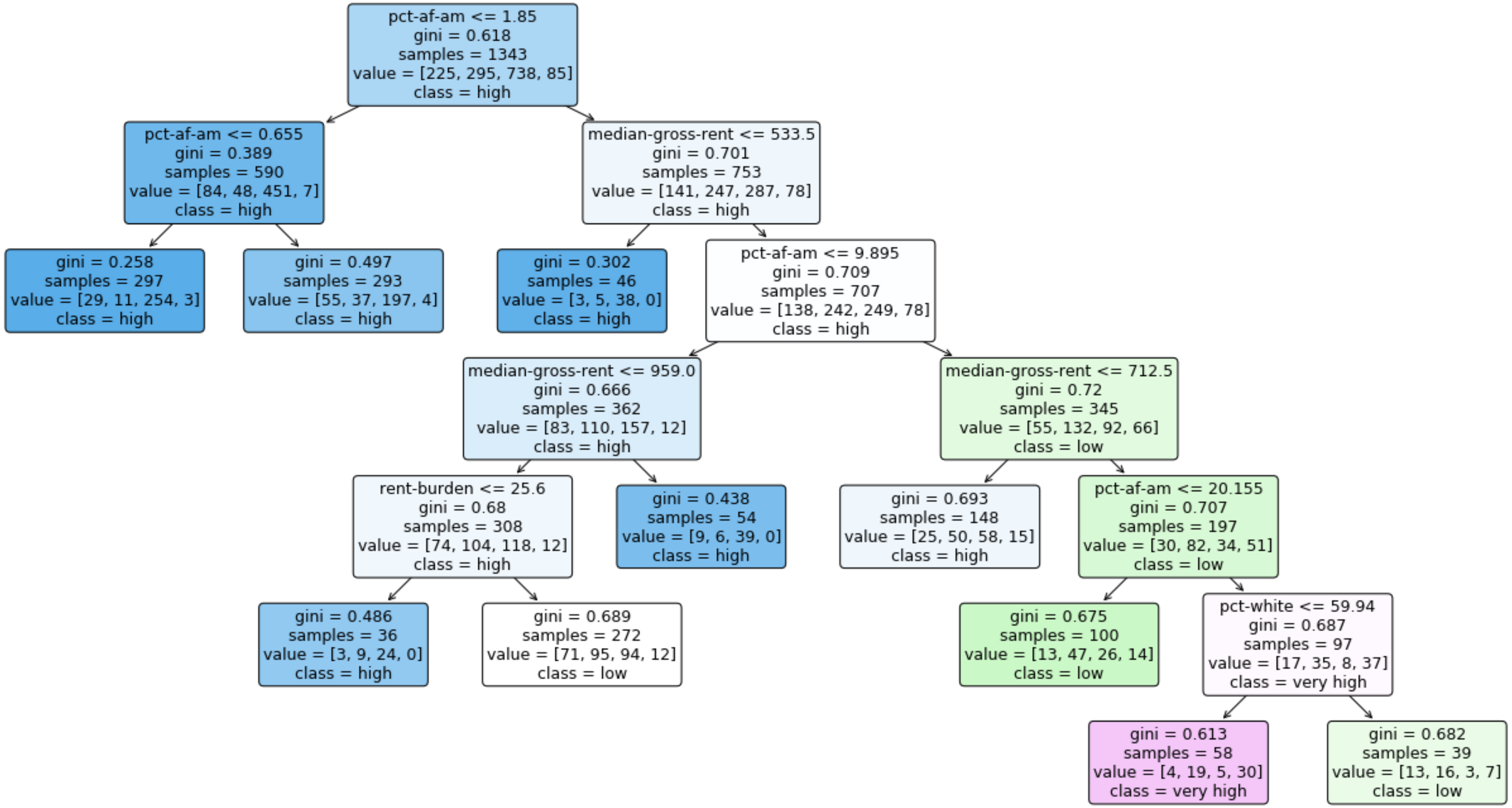
Out[87]:
```
low          352
average      711
high         407
very high    535
Name: suspension level, dtype: int64
```

Decision Tree Classification Algorithm for County Evictions

In [88]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, r2_score
from sklearn.tree import DecisionTreeClassifier, plot_tree
```

In [89]:

```
plt.figure(figsize=(22, 12))

X_evct = evct_susp[['poverty-rate', 'pct-renter-occupied', 'median-gross-rent', 'median-household-income', 'rent-burd
                'pct-white', 'pct-af-am', 'pct-hispanic']].copy()

y_evct = evct_susp['eviction level'].copy()


X_train, X_test, y_train, y_test = train_test_split(X_evct, y_evct, test_size=0.33, random_state=17)

evct_tree = DecisionTreeClassifier(max_leaf_nodes=10).fit(X_train, y_train)

evct_plot = plot_tree(evct_tree, feature_names=X_evct.columns, class_names=y_evct.values.unique(),
                 filled=True, rounded=True, fontsize=12.5)
```



In [90]:

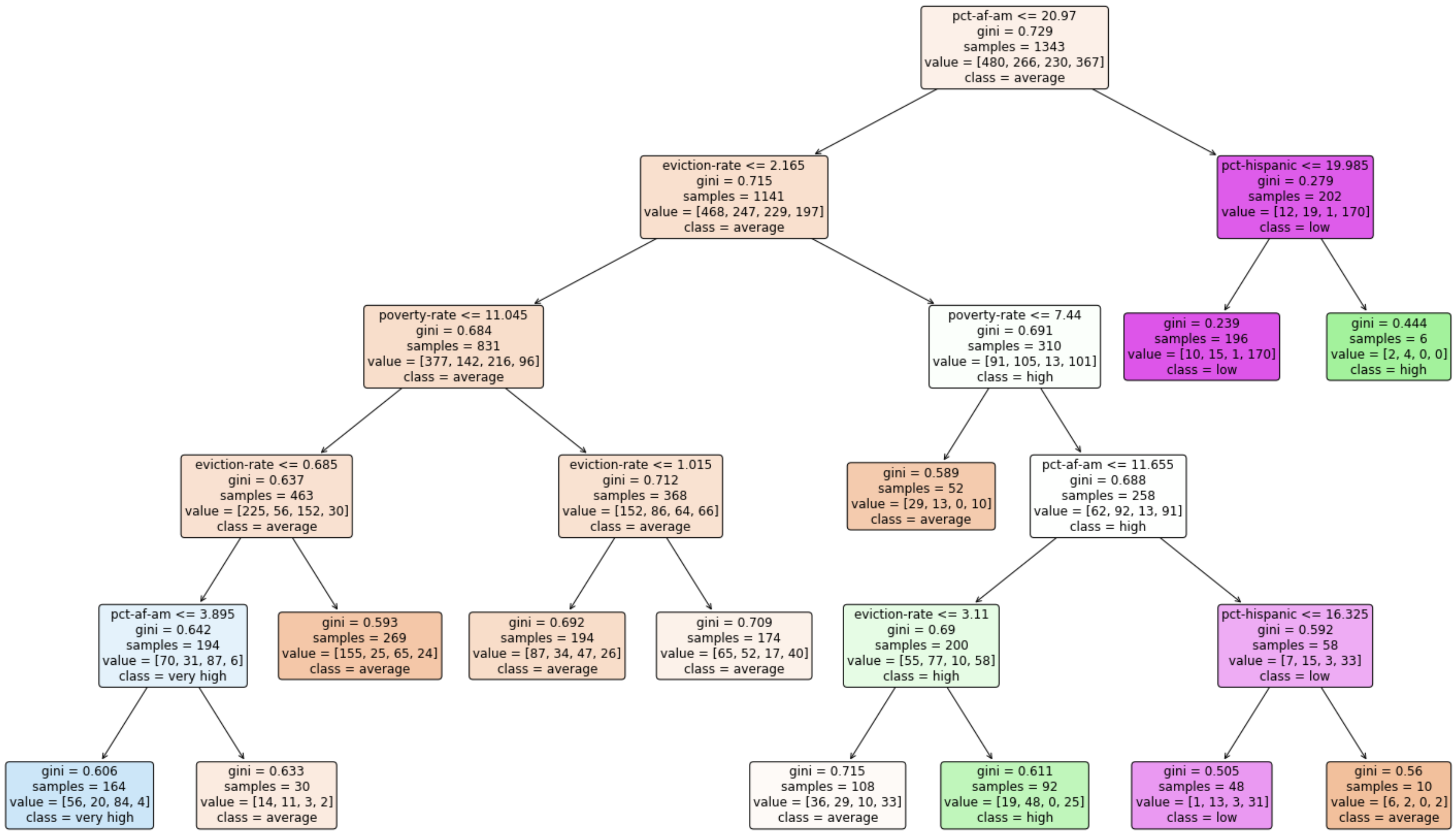
```
evct_preds = evct_tree.predict(X_test)

evct_preds_acc = accuracy_score(y_true=y_test, y_pred=evct_preds)
print('Eviction Level Decision Tree Accuracy Score:', evct_preds_acc)
```

```
Eviction Level Decision Tree Accuracy Score: 0.581570996978852
```

Decision Tree Classification for school suspensions using evictions data

In [91]:

```
plt.figure(figsize=(26, 16))

X_susp = evct_susp[['poverty-rate', 'pct-renter-occupied', 'median-gross-rent', 'median-household-income',
                   'pct-white', 'pct-af-am', 'pct-hispanic', 'eviction-rate']].copy()

y_susp = evct_susp['suspension level'].copy()


X_train, X_test, y_train, y_test = train_test_split(X_susp, y_susp, test_size=0.33, random_state=728)

susp_tree = DecisionTreeClassifier(max_leaf_nodes=12).fit(X_train, y_train)

susp_plot = plot_tree(susp_tree, feature_names=X_susp.columns, class_names=y_susp.values.unique(),
                      filled=True, rounded=True, fontsize=12)
```



In [92]:

```
susp_preds = susp_tree.predict(X_test)

susp_preds_acc = accuracy_score(y_test, susp_preds)
print('Suspension Level Decision Tree Accuracy Score:', susp_preds_acc)
```

```
Suspension Level Decision Tree Accuracy Score: 0.48338368580060426
```

Regression Model using Eviction Rates to Predict Suspensions

In [93]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

indicators = ['poverty-rate', 'eviction-rate', 'pct-renter-occupied', 'median-gross-rent',
                      'pct-white', 'pct-af-am', 'pct-hispanic']


X_susreg = evct_susp[indicators].copy()

y_susreg = evct_susp['Total_suspension rate'].copy()

X_train, X_test, y_train, y_test = train_test_split(X_susreg, y_susreg, test_size=0.33, random_state=185)


susreg = LinearRegression().fit(X_train, y_train)
y_susreg_preds = susreg.predict(X_test)

print('R-squared Value for predictions (coefficient of determination):', r2_score(y_test, y_susreg_preds))

# setting squared=False for MSE returns RMSE
print('Root Mean Squared Error (RMSE):', mean_squared_error(y_test, y_susreg_preds, squared=False))
```

```
R-squared Value for predictions (coefficient of determination): 0.38320267728015545
Root Mean Squared Error (RMSE): 0.18780580419708232
```

StatsModels is useful for Generating Linear Regression summary tables

Identify which variables have the strongest effect on suspensions, and their significance levels

Note that this regression model is run for the entire dataset without splitting into training and test sets

In [94]:
```
import statsmodels.api as sm

# Need to add constant to add y-intercept to the model
X_susreg = sm.add_constant(X_susreg)

smreg = sm.OLS(y_susreg, X_susreg).fit()
print(smreg.summary())
```

```
                            OLS Regression Results
==================================================================================
Dep. Variable:     Total_suspension rate   R-squared:                       0.371
Model:                               OLS   Adj. R-squared:                  0.369
Method:                    Least Squares   F-statistic:                     168.2
Date:                   Sun, 23 Aug 2020   Prob (F-statistic):         8.18e-196
Time:                           13:01:44   Log-Likelihood:                 407.94
No. Observations:                   2005   AIC:                            -799.9
Df Residuals:                       1997   BIC:                            -755.1
Df Model:                              7
Covariance Type:               nonrobust
========================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
const                   0.2939      0.097      3.025      0.003       0.103       0.484
poverty-rate            0.0051      0.001      4.000      0.000       0.003       0.008
eviction-rate           0.0271      0.003      9.860      0.000       0.022       0.033
pct-renter-occupied    -0.0008      0.001     -1.072      0.284      -0.002       0.001
median-gross-rent    2.559e-06     3.4e-05     0.075      0.940   -6.42e-05    6.93e-05
pct-white              -0.0024      0.001     -2.893      0.004      -0.004      -0.001
pct-af-am               0.0056      0.001      6.574      0.000       0.004       0.007
pct-hispanic           -0.0040      0.001     -4.360      0.000      -0.006      -0.002
==============================================================================
Omnibus:                     1832.831   Durbin-Watson:                   1.825
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           105799.469
Skew:                           4.116   Prob(JB):                         0.00
Kurtosis:                      37.622   Cond. No.                     1.63e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.63e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [ ]: