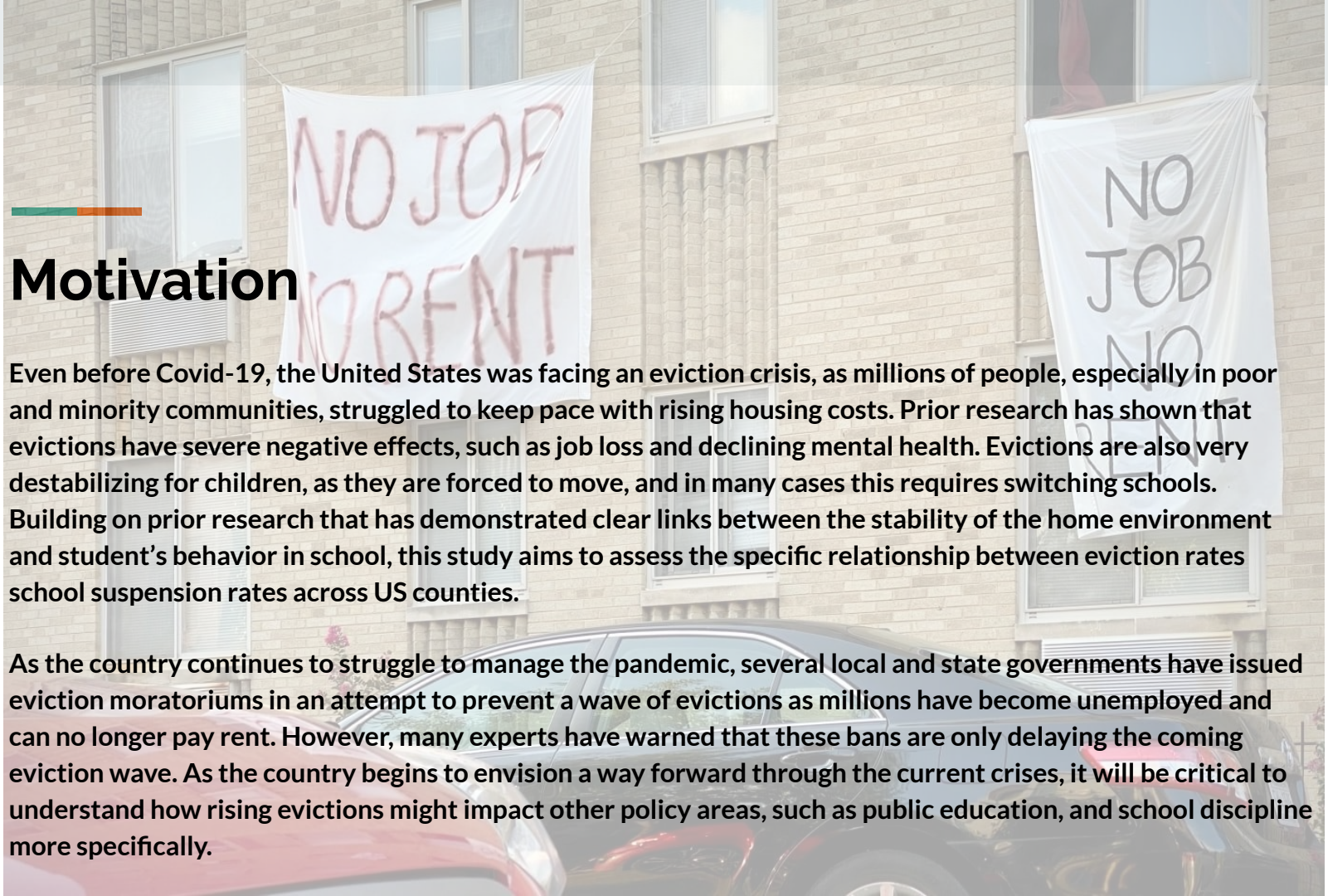
Kicked Out, Sent Home: Exploring the Relationship between Evictions and Out-of-School Suspensions

Chris Reed
DSE 200x

Abstract

This project sought to answer several important questions related to evictions and out-of-school suspensions. The first aim was to determine which factors were most relevant in predicting eviction levels (low, average, high, very high) based on census demographic data at the county level. A decision tree classification algorithm was used to train a classifier. The second aim was to test whether a relationship exists between eviction levels and school suspension levels (at the county level), and to determine if eviction levels were useful in predicting suspension levels. A decision tree classifier was used for this task as well. The final aim was to develop a model to estimate the effect of eviction levels on suspension rates. An OLS regression model was trained, which found a somewhat small but significantly positive relationship between eviction levels and suspension rates. Accuracy rates for the decision tree classifiers for eviction and suspension levels were .58 and .48, respectively.



Motivation

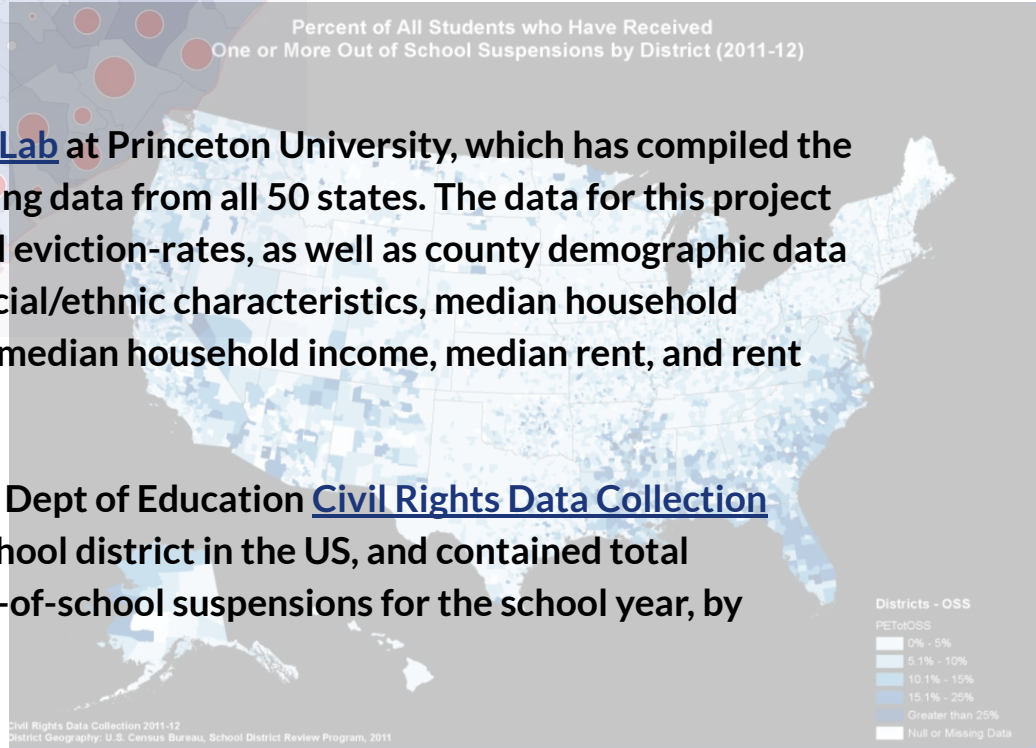
Even before Covid-19, the United States was facing an eviction crisis, as millions of people, especially in poor and minority communities, struggled to keep pace with rising housing costs. Prior research has shown that evictions have severe negative effects, such as job loss and declining mental health. Evictions are also very destabilizing for children, as they are forced to move, and in many cases this requires switching schools. Building on prior research that has demonstrated clear links between the stability of the home environment and student's behavior in school, this study aims to assess the specific relationship between eviction rates school suspension rates across US counties.

As the country continues to struggle to manage the pandemic, several local and state governments have issued eviction moratoriums in an attempt to prevent a wave of evictions as millions have become unemployed and can no longer pay rent. However, many experts have warned that these bans are only delaying the coming eviction wave. As the country begins to envision a way forward through the current crises, it will be critical to understand how rising evictions might impact other policy areas, such as public education, and school discipline more specifically.

Dataset(s)

Data for evictions comes from the Eviction Lab at Princeton University, which has compiled the first national database on evictions, gathering data from all 50 states. The data for this project used county-level statistics of evictions and eviction-rates, as well as county demographic data from the Cenesus Bureau (poverty level, racial/ethnic characteristics, median household income, percentage of renting households, median household income, median rent, and rent burden).

District suspensions data from from the US Dept of Education Civil Rights Data Collection office. The dataset included every public school district in the US, and contained total enrollment and total number of days of out-of-school suspensions for the school year, by racial/ethnic categories and by gender.



Data Preparation and Cleaning

Data on school suspensions was downloaded for each state, and then combined into a single DataFrame. This was merged with a separate geographic data from the Department of Education containing geographic data, using the distinct 'LEAID' number for each school district. ID's were converted to strings, so that 0's could be prefixed for ID's that were only 6 digits long.

A measure for suspension rates was calculated for each district by dividing the total number of school suspension days by the total enrollment. This is a measure of the average number of suspension days per student. For example: a district suspension rate of 1.5 means that on average, a student in the district was suspended for 1.5 days of the school year. The data was then grouped by county, and the average suspension rate for each county was calculated.

Load States Suspenions Data

In [2]:
```
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[2]:

	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

Data Preparation and Cleaning

County names were also formatted to include the state abbreviation, to avoiding grouping together counties with the same name in different states together (i.e. Jefferson County → Jefferson County, MO). The county average suspension rates DataFrame was then merged with the county evictions data on the county name, and rows with a suspension rate and eviction rate of 0 were removed. An initial analysis found little differences by gender, so the totals for male and female students for suspensions and enrollment were combined into single measures for all students.

Low, average, high, and very high categories were created using suspension and eviction rates, which were then used as the targets for the classification algorithms.

Research Question(s)

Q1: What characteristics are the strongest predictors of evictions?

Q2: Are eviction rates and suspension rates related? Can eviction rates be a useful predictor for classifying suspension levels?

Q3: What is the estimated effect (if any) of eviction rates and suspension rates?

Methods

A decision tree classifier was used to determine which demographic characteristics were the strongest predictors of eviction levels. Similarly, a decision tree classifier was trained using the county demographic and eviction rate data to predict county suspension levels, to determine if eviction levels were an effective predictor of suspension levels. For both, the decision trees were trained using 66% of the data, and tested with the remaining 33% for accuracy in predicting the four level categories.

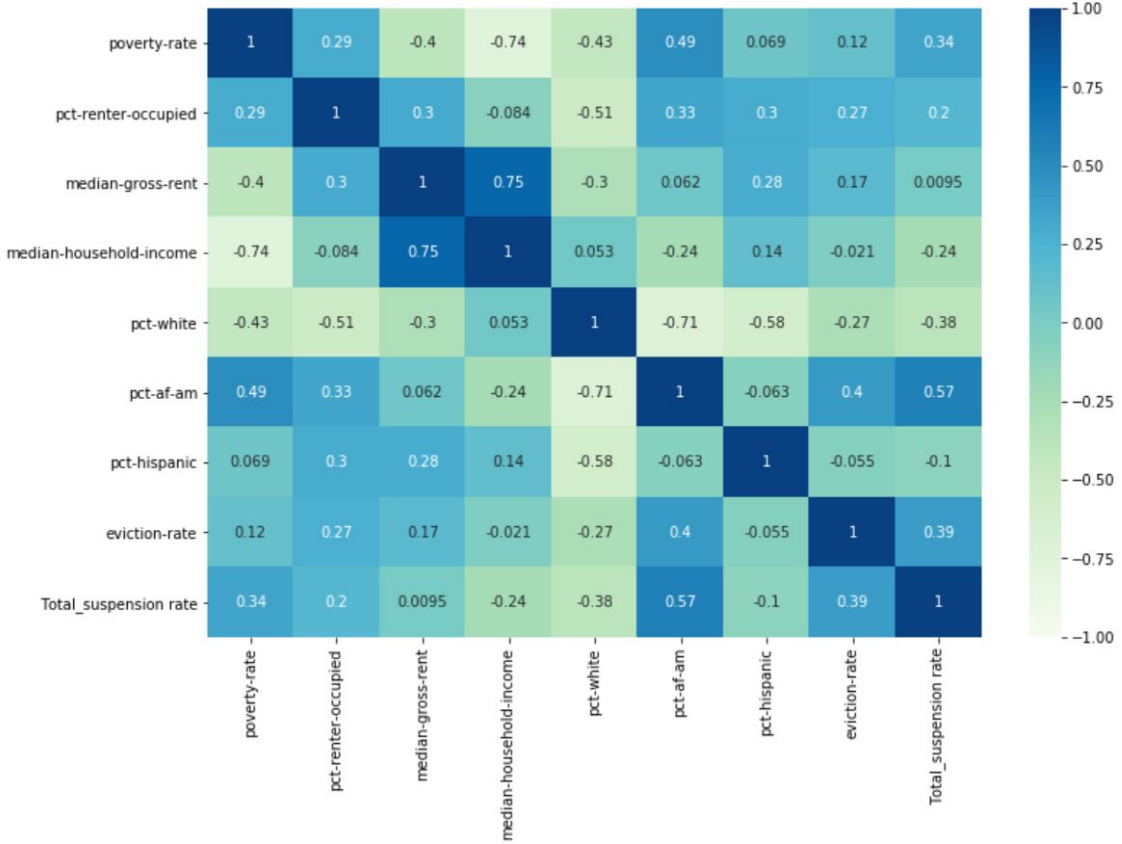
Lastly, an OLS regression model was developed to estimate the effects of eviction rates and other county demographic data on suspension rates. The regression model was used for this task instead of a classifier because suspension rates are a continuous variable, so the OLS model estimates the effects of a unit change in eviction rates on average county suspension rates. This model was also trained using the same split as above, and scored using the root mean squared error and the coefficient of determination for the model run on the test data.

Findings

The table on the right shows the correlation matrix, which was created using the Seaborn Heatmap. Strength of the correlations between pairs of variables of county demographic information and eviction and suspension rates. Interestingly, there is a very weak correlation between eviction rates and poverty rates, and a stronger correlation between eviction rates and the percentages of African-American in a county. Suspension rates were also most strongly correlated with percentages of African-Americans, suggesting issues of structural inequalities along racial lines.

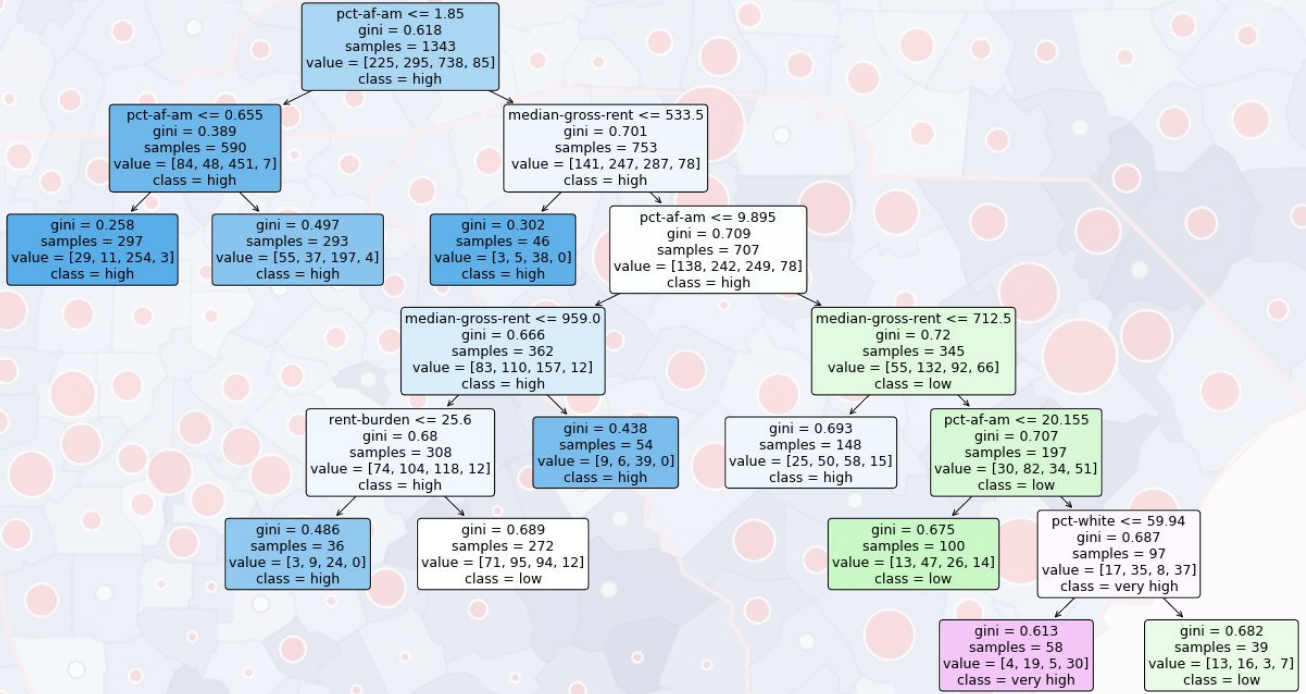
Correlation matrix of demographics, evictions data, and suspensions data

In [65]:
```
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')
```



Findings

This figure shows the decision tree classification algorithm for eviction levels. Each node is split with True values for the test condition (line at the top) placed in the left and False values for the test condition in the right. The tree shows that percentages of African-Americans was a significant feature, which speaks to the longstanding challenges of structural inequality along racial lines. The accuracy score for predictions was 0.58, which is moderately accurate, given the main features used by the tree.



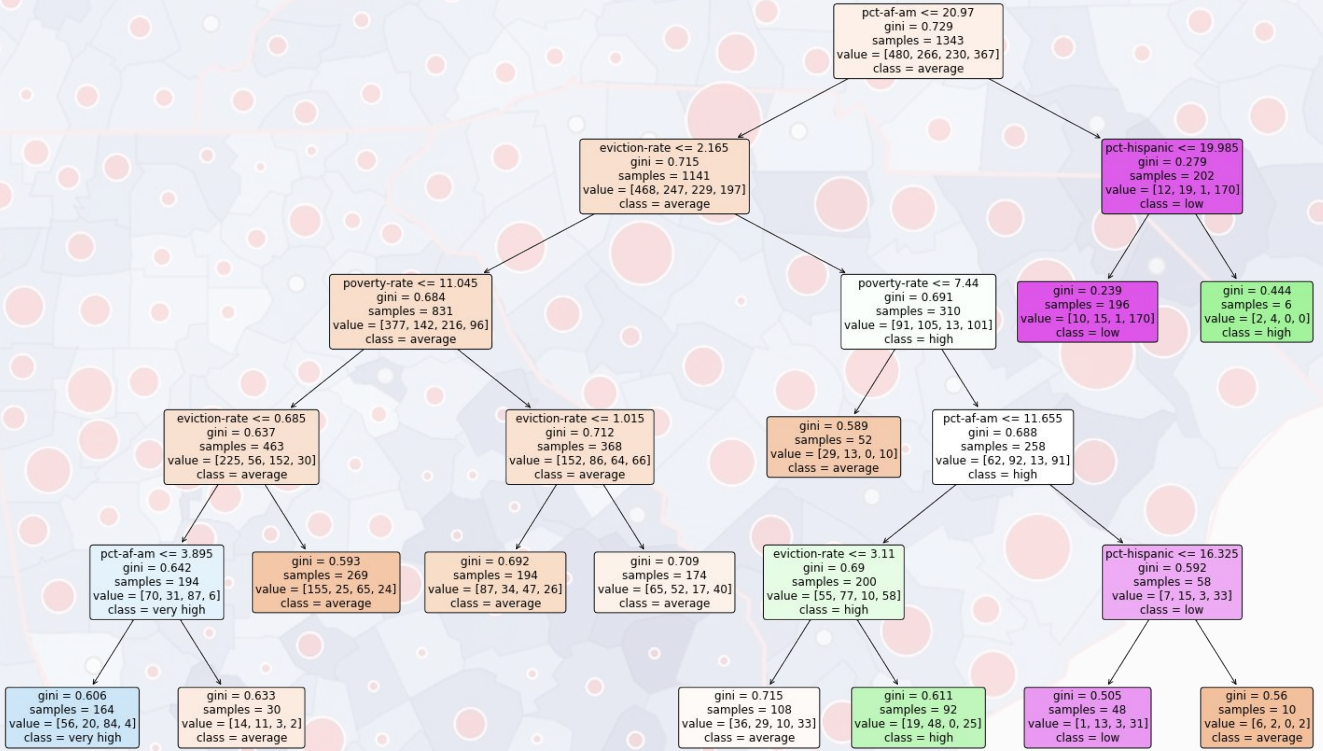
In [34]:

```
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
```

Findings

This plot shows the decision tree that was trained with the county demographic and evictions data to predict average county suspensions levels. Similarly to the evictions tree, percentages of African-Americans are an important feature, and the eviction rate is also important. The accuracy score for this tree was ten pct lower than the eviction levels tree, but it is still interesting that the classifier accurately predicts county suspension levels nearly half the time, using only demographic and evictions data.



In [60]:

```
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
```

Findings

The cell to the right shows the results of the OLS regression model that was trained using the same evictions/demographic data for the classification models, but instead of determining suspension levels, the regression model estimates the effects of the indicators on suspension rates. The R-squared value of .38 shows that 38% of the variation in county suspension rates can be predicted using the county demographic/eviction data, without any additional district data. This demonstrates that education policies cannot be separated from wider socioeconomic issues in communities.

Regression Model using Eviction Rates to Predict Suspensions

In [49]:

```
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
```

Findings

Finally, an additional OLS regression was run on the full dataset, using the StatsModels library, which provides a convenient summary method to generate regression results for each of the input variables (coef), with standard errors and statistical significance ($p < .05$). The R-squared for the full model is only .01 less than the OLS model run on the test data, and the table showing coefficients for each input variable shows that eviction rates had the strongest effect; a unit increase in eviction rates is associated with an increase in suspension rates of .0271, which is statistically significant ($p < .001$). Results from the regression models provide clear evidence that there is a relationship between eviction rates and suspension rates, with an increase in the former being associated with an increase in the latter.

In [50]:

```
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:                           08:50:22   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.
```

Limitations

One of the major limitations, which has been acknowledged by the Eviction Lab, is that the data they have gathered only captures evictions that have gone through the legal process, where a landlord formally filed an eviction with the courts. As the authors of the project note, in many areas the number of “informal” evictions may be much higher, as landlords offer tenants cash to move out or push renters out by other, more aggressive and illegal means. As such, the results of the current study may underestimate the true effect of evictions on school suspensions, as many families that have been evicted may not be reflected in the available data.

An additional challenge for this study was determining the appropriate geographic unit to match suspensions and evictions data. For smaller counties with one district, average suspension rates were simply the rate for that district, but for larger counties, with multiple districts (urban/suburban for example), the average rate for the entire county may obscure important difference between different areas within the county.

Conclusions

The results of this project demonstrate a clear relationship between evictions and school suspensions, in line with previous research that a lack of stability has significant and negative impacts on the wellbeing of children (Sandstrom and Huerta, 2013). Findings also demonstrate evidence, also in line with decades of research on social inequalities, of a racial gap between black and white families for evictions and suspensions. The results from the classification and regression models demonstrate that educational policies related to school discipline must take into account factors in the community beyond the schools, which can have a significant impact on what happens within the schools. If 38% of school suspension rates can be explained by factors completely outside of district-level characteristics, then it is the responsibility of district and local housing and social services agencies to begin working together to address the issues of housing instability, and to better understand how such issues can impact students' behaviors in schools. As the US potentially faces a wave of evictions resulting from the Covid-19 economic downturn, a better understanding of this relationship will be critical to developing policies to ensure that students and families aren't further destabilized as communities struggle through the pandemic.

Acknowledgements

Data were gathered from the Eviction Lab and the Dept of Education's Civil Rights Data Collection office. Many thanks are owed to family members and my wife for their valuable feedback and interest in the project as I went through.

And as always with any data science project, many thanks is owed to the StackOverflow community, which has never failed to provide essential help and elegant programming solutions, to all of the common python/pandas/sklearn issues I came across when doing the analysis.

References

Gopalan, M., & Nelson, A. A. (2019). Understanding the Racial Discipline Gap in Schools. AERA Open. https://doi.org/10.1177/2332858419844613

https://academic.oup.com/sf/article-abstract/98/4/1548/5521044?redirectedFrom=fulltext#136963430

https://www.washingtonpost.com/business/2020/07/06/eviction-moratoriums-starwood/

https://www.npr.org/2018/12/17/677508707/suspensions-are-down-in-u-s-schools-but-large-racial-gaps-remain

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)

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]:

```
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 CEN 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 CEN 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 CEN 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 CEN 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]:

```
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/)

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	eviction 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	eviction 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]:

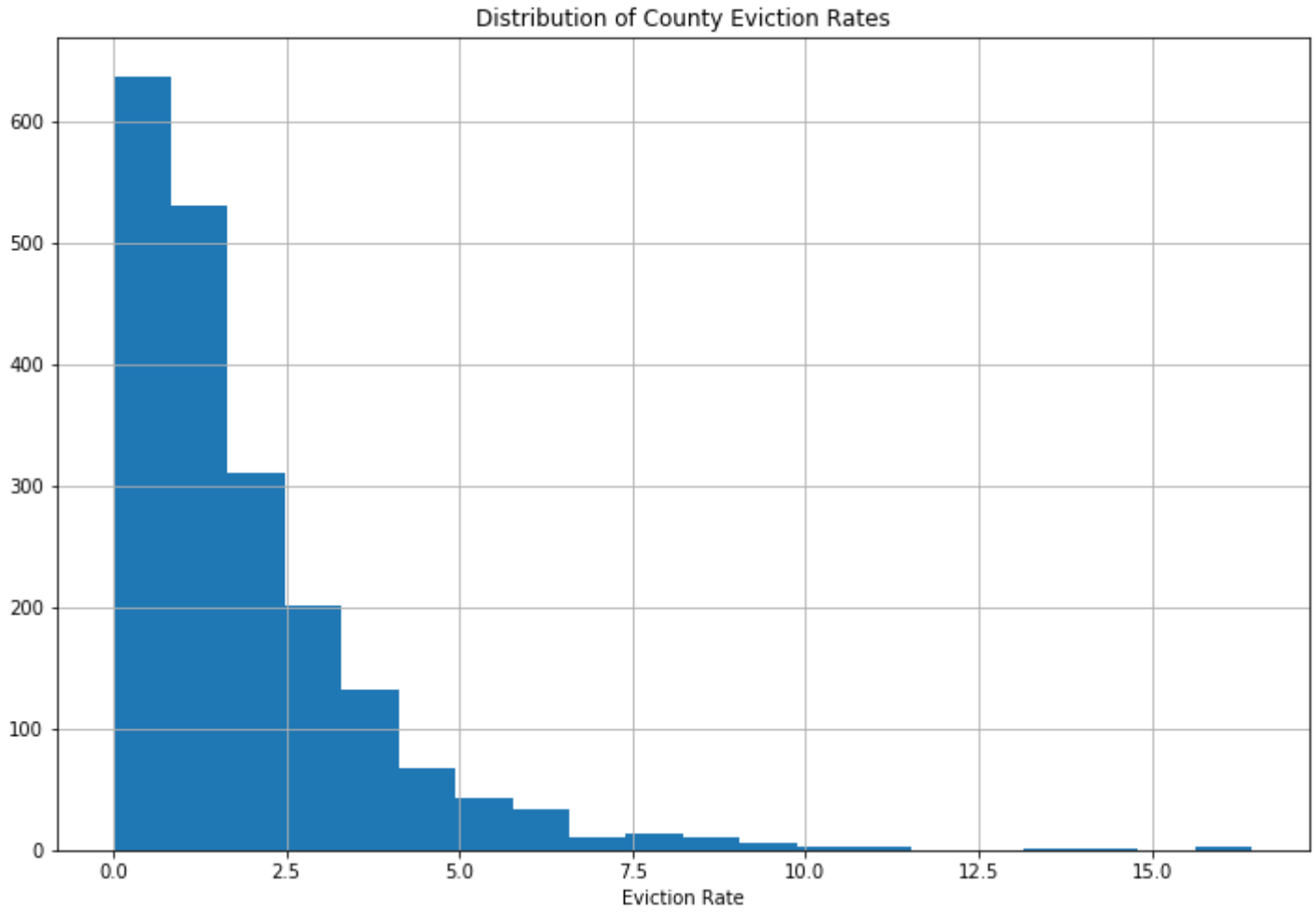
	population	poverty-rate	renter-occupied-households	pct-renter-occupied	median-gross-rent	median-household-income	median-property-value	rent-burden	pct-white	pct
count	2.005000e+03	2005.000000	2.005000e+03	2005.000000	2005.000000	2005.000000	2005.000000	2005.000000	2005.000000	2005.(
mean	1.247259e+05	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

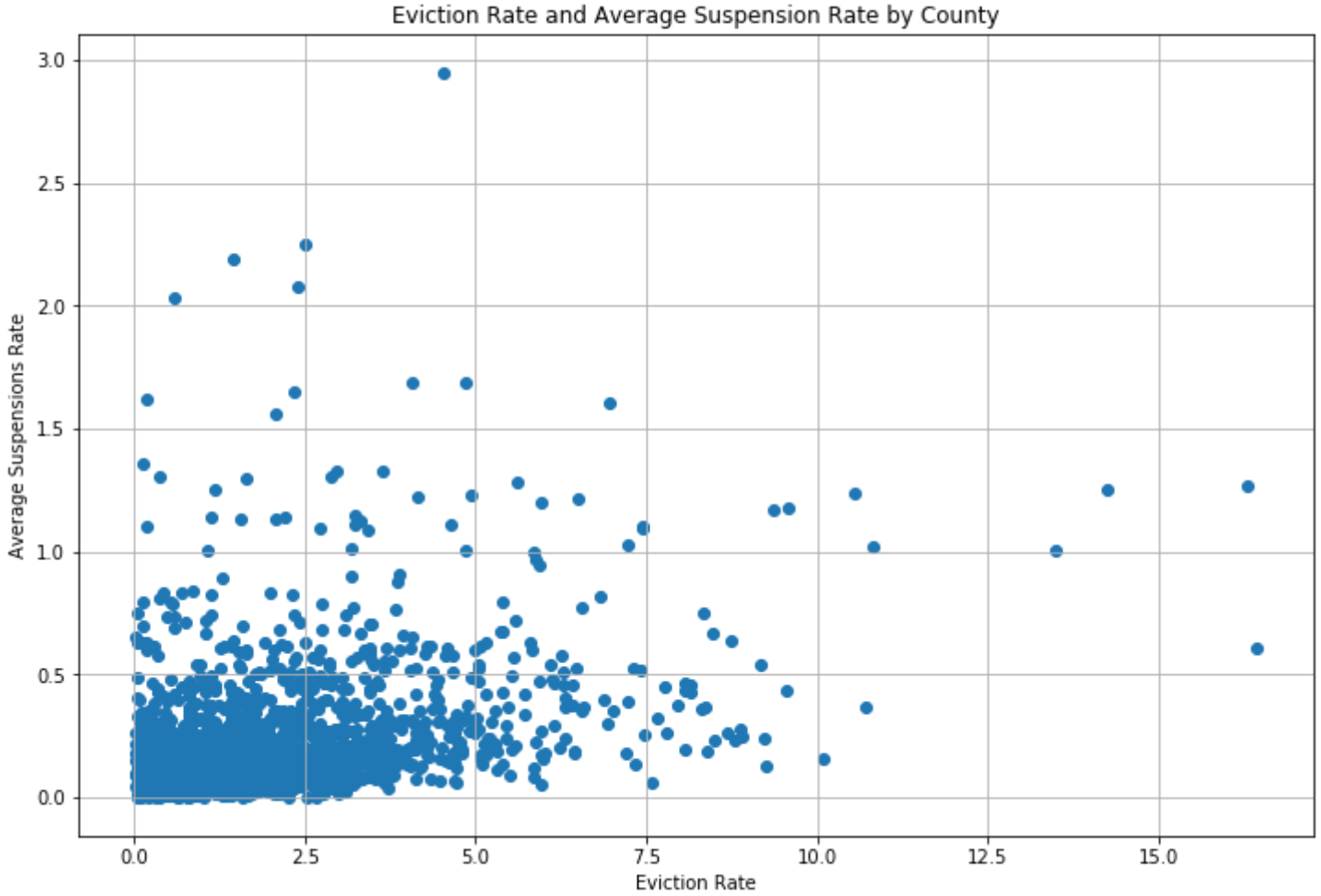
In [82]:

```
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.

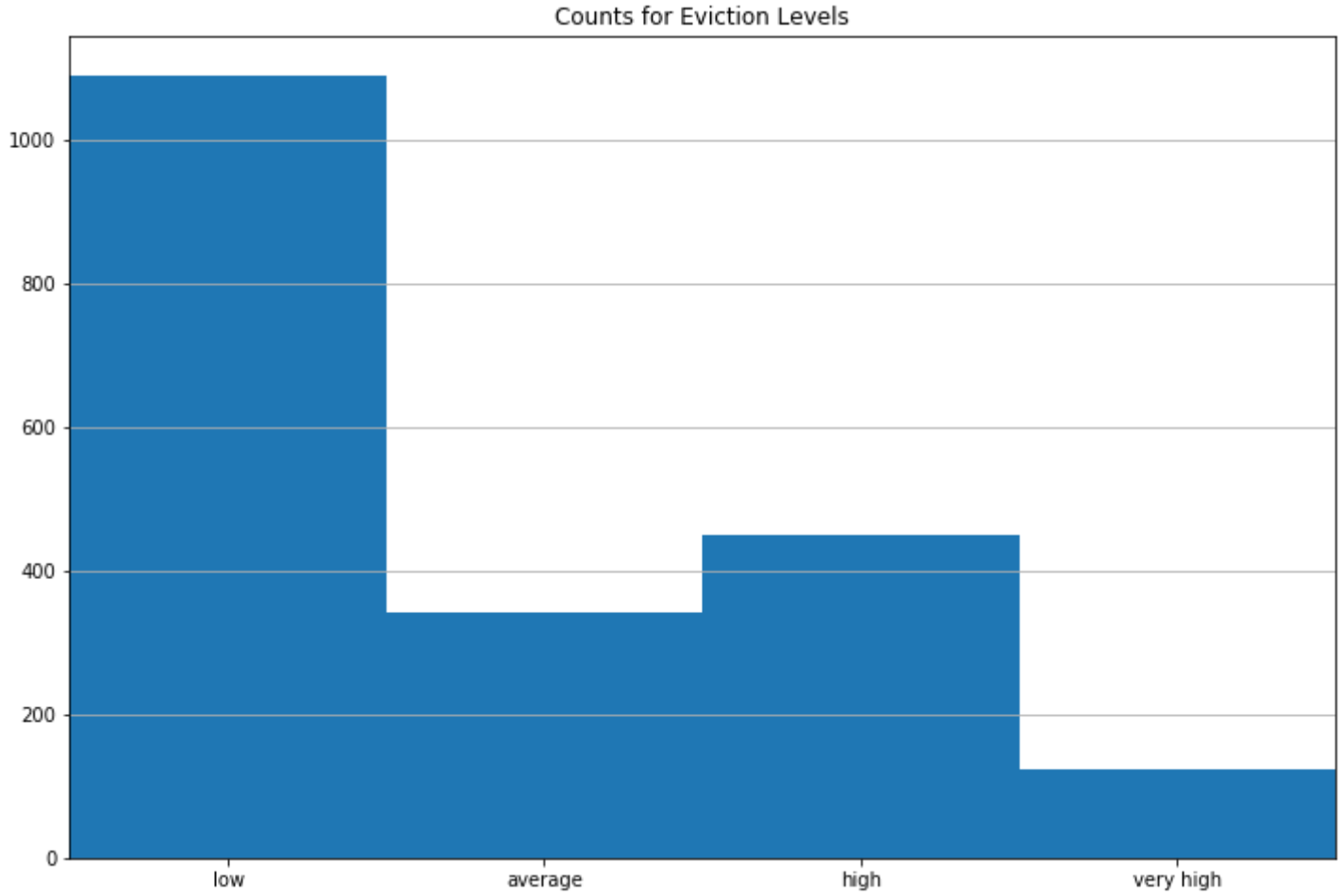
In [84]:
```
evct_susp[['eviction-rate']].describe()
```

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]:

```
# 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
1000
800
600
400
200
0
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()
```

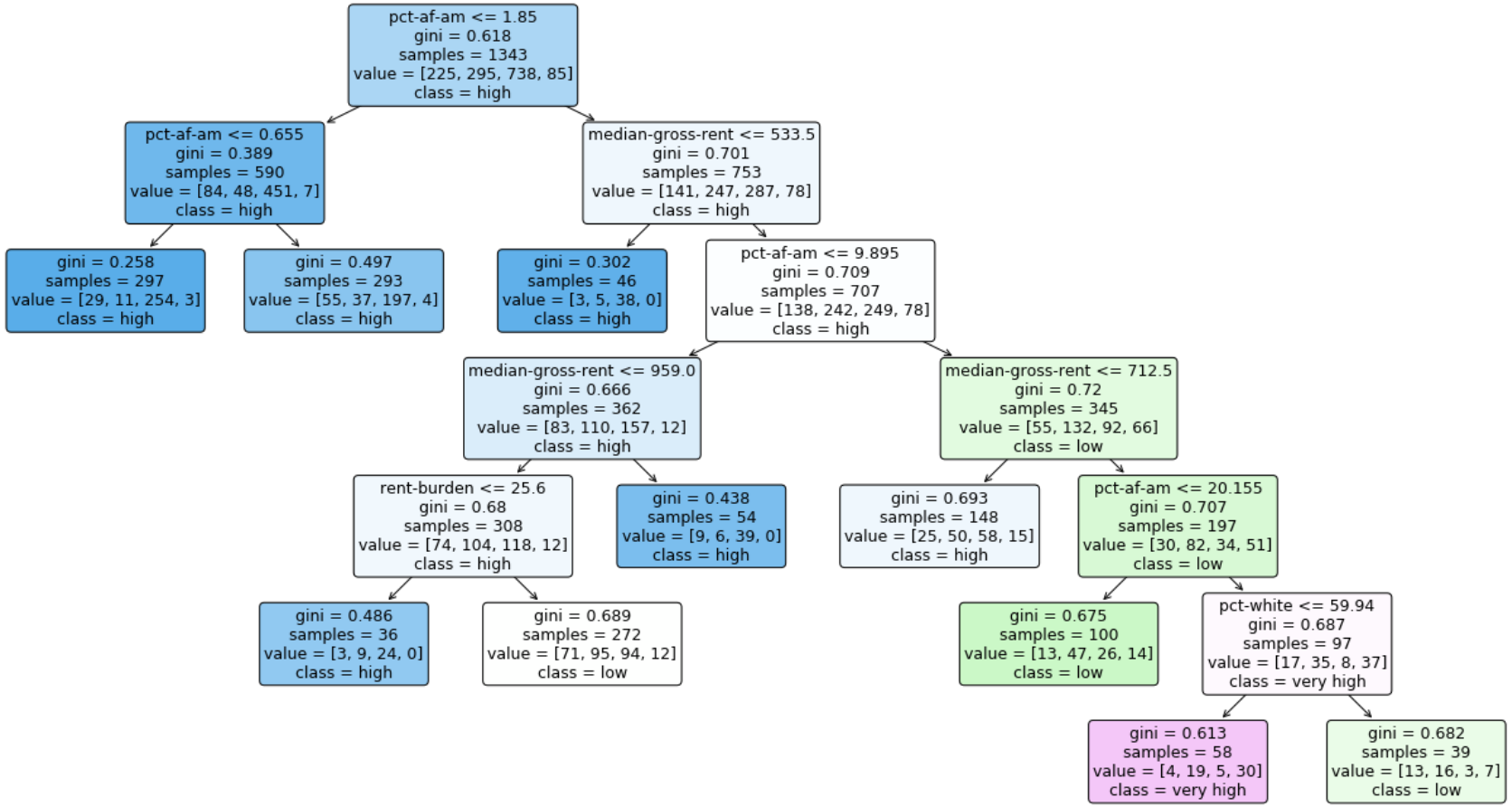
Out[87]:
```
low          352
average      711
high         407
very high    535
Name: suspension level, dtype: int64
```

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]:

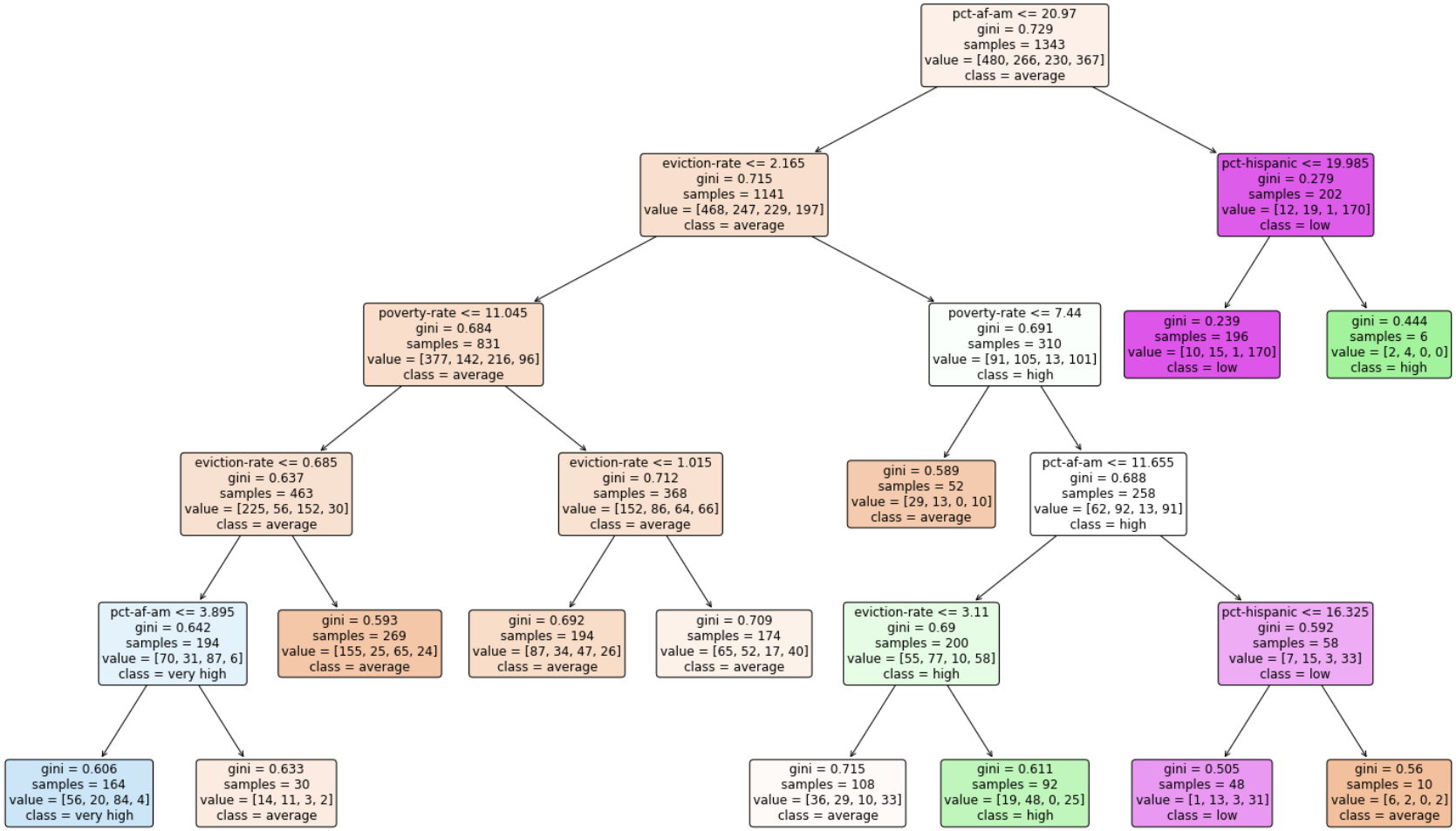
```
evct_preds = evct_tree.predict(X_test)

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 [ ]: