FinalProject

June 12, 2019

1 COGS 108 - Final Project

2 Overview

As a group, we wanted to dig deeper into whether or not there was any association between income inequality and the level of crime experienced in different cities in the United States. As we explored our data and applied tests to said data, we saw that there was indeed a difference in crime rates between areas that did versus did not experience income inequality. However, upon further testing, we saw that the correlation between income inequality and crime was quite weak, making income inequality a weak predictor for crime index.

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4 Research Question

We want to shed light on the effects of economic inequality on society, and see if it has any effect on crime rates. We can tackle this topic from a data science perspective by narrowing down the question a bit more. The data science question we are asking is the following: What is the correlation between street crime and economic inequality in the US?

There are some important things to note about how we defined our terms. Firstly, the kind of crime we are looking at includes forms of violent crime and street crime - things like muggings, theft, and even murder. We are not currently interested in things like speeding or white collar crime.

Secondly, we are looking at economic inequality, not poverty. While it is fairly obvious that poverty and crime are related (with desperation comes drastic measures), we are trying to tease out the effect of income inequality in and of itself. It could be that inequality contributes to the disintegration of communities and crime in a fashion that is independent from the sheer effect of poverty. Perhaps one community might have more crime in it than another even though they both have similar levels of poverty, due to the fact that the one community has a substantial level of inequality. Indeed, it's possible that an unequally distributed increase in wealth could catalyze an upswing in crime. This will no doubt require close inspection to properly disambiguate the effects of poverty from the effects of inequality.

4.1 Background and Prior Work

Due to developments in our current political climate, discussion about the harms of income inequality has become increasingly prevalent. Popular politicians such as Alexandria Ocasio-Cortez and Bernie Sanders have shined the floodlights on the glaring cleft that lies between the richest Americans and the rest of us. A quick look at the numbers will show that the divide between rich and poor is growing in this country (1). With the advent of this apparent fact, many have begun researching the various ways in which increased income inequality affects society.

We're not the first group of people to investigate the relationship between crime and income inequality. According to David Luther from Zippia, in 2016, the FBI released crime rate statistics that showed correlation between city crime and income inequality (2). The study looks at FBI data about property crime and violent crime and concluded that income inequality correlates the strongest with crime compared to other variables such as unemployment, poverty, and number of high school graduates where there was only weak correlation. In this paper, the results also show that robbery and burglary in the US are strongly affected by income inequality (3). On a larger scale, this journal article also describes how violent crime and income inequality are positively correlated when looking at different countries (4).

We can add something of value to the larger conversation by comparing analyses with two different metrics of income inequality. We will be using the quintile share and the gini index, which are both reliable, trusted ways of measuring income inequality. (discussed more in the Data section below). And while it may not constitute the bulk of our analysis, we will also be able to take a brief look at how income inequality influences different kinds of crime, since we have data not just about the general crime levels, but also about the amounts of particular kinds of crime including theft, murder, arson and burglary.

References (include links): - 1) U.S. Income Inequality: Facts, Causes, Solutions:
https://www.thebalance.com/income-inequality-in-america-3306190

- 2) New FBI Data Correlates City Crime to Income Inequality:

https://www.zippia.com/advice/crime-income-inequality/

- 3) Income inequality and crime in the United States:

https://tinyurl.com/y6t7cegl

- 4) Inequality and Violent Crime:

https://www.jstor.org/stable/10.1086/338347?seq=1#page_scan_tab_contents

5 Hypothesis

We expect to find a positive correlation between the rate of street crime and economic inequality in the US. There are news articles all over the internet that speculate about this particular correlation. It is a relationship that governments, organizations, economists, and sociologists have all studied a fair amount. In particular, as stated in the NYU Dispatch's article "How big is income inequality as a determinant of crime rates?" from May 23, 2018, "[a] 2002 study by The World Bank found that crime rates and inequality are positively correlated, and an increase in income inequality has the effect of intensely increasing crime rates."

6 Dataset(s)

6.0.1 Summary of Data and Combining

We found three datasets to help answer our question: US Household Income, US Crime, and US Gini Index. Our datasets were either web scraped from a website that has aggregated information from public records or downloaded from the US Census Bureau FactFinder. We combined the crime and household datasets by merging them based on city and state values. The Gini Index and crime datasets were also merged based on city and state. Since the web scraping was done in parts, some of the export csv names may differ from the final csv/dataset names.

6.0.2 Household Income Dataset

- Dataset Name: economic_data.csv
- Link to the dataset: https://statisticalatlas.com/United-States/Household-Income#top
- Number of observations: 10872

The US household income data was web scraped from Statistical Atlas which uses data from the US Census Bureau, specifically the 2010 census and the 2012-2016 American Community Survey. For each city we scraped the city name, state name, percentile, income, and percent (as percentage of median household income).

Web Scraping for US Household Income Data

```
In [ ]: """
        This script gets the URL to the page of every major city in the US. It searches by
        state.Once it collects all of those URLS, then those URLS can be fed into the
        scrape_statistical_atlast.py fileso that we can scrape up the data for every city.
        Author: Samuel Parker
        """
        import gzip
        import bs4
        import urllib.request
        import pandas as pd
        import pickle
        import os
        import re
```

```python
states = ["Alabama","Alaska","Arizona","Arkansas","California","Colorado",
          "Connecticut","Delaware","Florida","Georgia","Hawaii","Idaho",
          "Illinois","Indiana","Iowa","Kansas","Kentucky","Louisiana","Maine",
          "Maryland","Massachusetts","Michigan", "Minnesota","Mississippi",
          "Missouri","Montana","Nebraska","Nevada","New-Hampshire","New-Jersey",
          "New-Mexico","New-York","North-Carolina","North-Dakota","Ohio",
          "Oklahoma","Oregon","Pennsylvania", "Rhode-Island","South-Carolina",
          "Tennessee","Texas","Utah","Vermont","Virginia","Washington",
          "West-Virginia","Wisconsin","Wyoming"]

url_base = 'https://statisticalatlas.com/state/'
url_list = []

for state in states:
    try:
        target_url = url_base + state + "/Overview"
        request = urllib.request.Request(
            target_url,
            headers={
                "Accept-Encoding": "gzip",
                "User-Agent":
                "Mozilla/5.0 (X11; U; Linux i686) Gecko/20071127 Firefox/2.0.0.11",
            })
        response = urllib.request.urlopen(request)
        gzip_dec = gzip.decompress(response.read())
        print(gzip_dec)
        gzipFile = gzip.GzipFile(fileobj=response)
        gzipFile.read()

        soup = bs4.BeautifulSoup(gzip_dec,features="lxml")

        vaart_steg = soup.find_all('div', class_="info-table-contents-td col-sm-9")
        vaart_steg = vaart_steg[3]
        vaart_steg = vaart_steg.find_all('a')
        hrefs = []
        for link in vaart_steg:
            if link != None:
                hrefs.append(link['href'])

        url_list += hrefs

    except:
        print("This state didn't work :( %s" %state)

# The URL for each list was put onto a big list.
# this list was serialized / pickled out and handled by another script
#(I have included it below)
pickle_out = open("city_hrefs","wb")
```

```python
pickle.dump(url_list,pickle_out)
pickle_out.close()

"""
Bin_breaker.py file. This was used to break up a list of stuff (like h-refs)
and break it up into a certain number of chunks. This easened the task of
scraping by not needing to do it all at once.
This script would be run once
Author: Samuel Parker.
"""
import pickle

pickle_in = pickle.load(file=open("county_hrefs","rb"))

def Break_bin (breakable, bin_count, filnamn):
    storage = {}

    for number in range(bin_count):
        storage[number] = []

    count = 0
    overLength = len(breakable)
    for number in range(len(breakable)):
        storage[count].append(breakable[number])
        count += 1
        if count % bin_count == 0:
            count = 0

    totala_laengden = 0
    count = 0
    for key in storage:
        stycket = storage[key]
        totala_laengden += len(stycket)
        pickle_out = open( (filnamn+str(count)), 'wb')
        pickle.dump(stycket, pickle_out)
        pickle_out.close()
        count += 1

    assert totala_laengden == overLength

Break_bin(pickle_in,8,"scrape_assignment")

""""
    scrape_statistical_atlas.py file.
    This file was used to scrape data about houssehold income
     off of statisticalatlas.com

     This script would be run once for each scraping assignment
```

```
    that I created using the binbreaker earlier. In our case,
    we had it run 8 times.

    Author: Samuel Parker
    Approximate date of use: Spring 2019
"""
# Importing libraries.
import gzip
import bs4
import urllib.request
import pandas as pd
import pickle
import os
import time

url_base = 'https://statisticalatlas.com'

## I had broken up the scraping assignments up in the binbreaker.
##That we don't have to scrape literally all of the data at once.
pickle_in = pickle.load(file=open("scrape_assignment7","rb"))

for k in pickle_in:
    print(k)

URLZ = []
Allting = {}

for pickled in pickle_in:
    ny_straeng = pickled[:len(pickled)-8]
    ny_straeng = ny_straeng + "Household-Income"
    ny_straeng =  url_base + ny_straeng
    URLZ.append(ny_straeng)

for straeng in URLZ:
    ## Using a try-catch block, so one exception doesn't
    ## jeopardize the whole operation.
    try:
        print(straeng)
        request = urllib.request.Request(
            straeng,
            headers={
                "Accept-Encoding": "gzip",
                "User-Agent":
                "Mozilla/5.0 (X11; U; Linux i686) Gecko/20071127 Firefox/2.0.0.11",
            })
        response = urllib.request.urlopen(request)
        gzip_dec = gzip.decompress(response.read())
        print(gzip_dec)
```

```
        gzipFile = gzip.GzipFile(fileobj=response)
        gzipFile.read()

        soup = bs4.BeautifulSoup(gzip_dec,features="lxml")

        vaart_steg = soup.body
        vaart_steg = vaart_steg.find("div",class_="figure-container",
                                     id="figure/household-income-percentiles")
        vaart_steg = vaart_steg.find("div", class_="figure-contents")
        vaart_steg = vaart_steg.find("svg")

        contents = vaart_steg.find_all("g")
        contents = [a.text for a in contents]

        Allting[straeng] = contents
        print(type(Allting))
        time.sleep(1)

    ## Handling exceptions
    except Exception as e:
        print(ny_straeng + " didn't work")
        print(e)

     #Saving it
filnamn = 'allting_scraped8'
pickle_out = open(filnamn,'wb')
print(type(Allting))
pickle.dump(Allting,pickle_out)
pickle_out.close()

"""
    remerge.py file. This file was used to merge back together chunks
    of scraped data.During the scraping process, I decided to scrape
    one eighth of all of the cities or counties at a time, and in this
    file, that sraped data gets put back together.
    Author: Samuel Parker
"""
import pandas
import pickle
pickle_in = pickle.load(file=open("city_hrefs","rb"))

url_base = 'https://statisticalatlas.com'
URLZ = []

for pickled in pickle_in:
    ny_straeng = pickled[:len(pickled)-8]
    ny_straeng = ny_straeng + "Household-Income"
    ny_straeng =  url_base + ny_straeng
```

```
    URLZ.append(ny_straeng)

HuvudOrdBoken = {}

dic1 = pickle.load(file=open("allting_scraped1","rb"))
dic2 = pickle.load(file=open("allting_scraped2","rb"))
dic3 = pickle.load(file=open("allting_scraped3","rb"))
dic4 = pickle.load(file=open("allting_scraped4","rb"))
dic5 = pickle.load(file=open("allting_scraped5","rb"))
dic6 = pickle.load(file=open("allting_scraped6","rb"))
dic7 = pickle.load(file=open("allting_scraped7","rb"))
dic8 = pickle.load(file=open("allting_scraped8","rb"))

# swedish for  word-book's list , e.g. dictionary list
ordboksLista = [dic1,dic2,dic3,dic4,dic5,dic6,dic7,dic8]

for underOrdbok in ordboksLista:
    for nyckel in underOrdbok:
        HuvudOrdBoken[nyckel] = underOrdbok[nyckel]

# At this point, we have a dictionary full of entries
# that contain all of our data.
pickle_out = open("remerged_data_county","wb")
pickle.dump(HuvudOrdBoken,pickle_out)
pickle_out.close()

"""
This file takes in the data that has been freshly scraped, and spits it out
into a CSV. The CSV would still be in need of more preprocessing, however.
But this is a first step.
"""
import pickle
import pandas as pd
import numpy as np
import os

percentiles = ["95th","80th","60th","Median","40th","20th"]
pickle_in = pickle.load(file=open("remerged_data_county","rb"))
data_ramar = []
for nyckel in pickle_in:
    try:
        place = []
        income = []
        percent = []
        namn_rad = []
        contents = pickle_in[nyckel]
        data_ram = pd.DataFrame(columns=['place', 'percentile',
                                         'income', 'percent'])
```

```
            for a in contents:
                if "Percentile" in a or "Median" in a:
                    #percentiles.append(a)
                    pass
                elif "$" in a:
                    income.append(pd.Series(a.split('$')[1]))
                elif "%" in a:
                    percent.append(pd.Series(a.split("%")[0]))
                namn_rad.append(nyckel)

            income = income[1:]
            namn_rad = namn_rad[:6]
            income = pd.Series(income)
            percent = pd.Series(percent)
            percentile = pd.Series(percentiles)
            namn_rad = pd.Series(namn_rad)
            data_ram.income = income
            data_ram.percent = percent
            data_ram.percentile = percentiles
            data_ram.place = namn_rad
            data_ramar.append(data_ram)
        except:
            print("This gave us trouble: ")
            print(nyckel)

    oever_dr = pd.concat(data_ramar)

    oever_dr.to_csv("income_county.csv")

    print(oever_dr)
```

6.0.3 US Crime Dataset

- Dataset Name: UScrime_scraped.csv
- Link to the dataset: http://www.city-data.com/crime/index.html
- Number of observations: 9865

The data on US city crime was web scraped from City-Data which uses data from public records and agencies. Data for 9865 cities was scraped and 19 features for each city were collected (city, state, murders, rapes, burglarys, assaults, crime index, and more). There are total numbers of crimes committed per city, crimes per 100,000 population, and a crime index which is a value that gives more weight to certain crimes (for instance murder is weighted more heavliy than assault).

Web Scraping for US Crime Data

```
In [ ]: from bs4 import BeautifulSoup as bsoup
        import requests as rq
```

```python
import re
import time
import random

# Create empty arrays to fill with data
city = []
state = []
murders = []
murdersper = []
rapes = []
rapesper = []
robberies = []
robberiesper = []
assaults = []
assaultsper = []
burglaries = []
burglariesper = []
thefts = []
theftsper = []
auto_thefts = []
auto_theftsper = []
arsons = []
arsonsper = []
crime_index = []

# Array for city links while scraping each state
links = []

# No crime data for Hawaii
# States with only one link
states = ['Alaska', 'Alabama', 'Arkansas', 'Arizona', 'Colorado', 'Connecticut',
          'Delaware', 'Iowa', 'Idaho','Indiana', 'Kansas', 'Kentucky', 'Louisiana',
          'Maine', 'Maryland', 'Massachusetts',  'Minnesota', 'Mississippi',
          'Montana', 'Nebraska', 'Nevada', 'New-Hampshire',  'New-Mexico',
          'North-Carolina', 'North-Dakota',  'Oklahoma', 'Oregon','Rhode-Island',
          'South-Carolina', 'South-Dakota', 'Tennessee','Utah','Vermont',
          'Virginia', 'Washington', 'West-Virginia', 'Wyoming']

# States with multiple links
multstates = ['California', 'California2','Florida' , 'Florida2','Georgia',
              'Georgia2', 'Illinois','Illinois2', 'Illinois3', 'Illinois4' ,
              'Michigan', 'Michigan2', 'Missouri', 'Missouri2','New-Jersey',
              'New-Jersey2', 'New-York', 'New-York2','Ohio', 'Ohio2',
              'Pennsylvania','Pennsylvania2', 'Pennsylvania3', 'Texas',
              'Texas2', 'Texas3', 'Wisconsin', 'Wisconsin2']

# Loop through all of the states (this was done in two parts
# with states and multstates)
```

```
for currstate in multstates:
    # Make a get request
    response = rq.get('http://www.city-data.com/crime/crime-' +
                      currstate + '.html', proxies=proxies)

    # Get the html for the state page
    page_html = bsoup(response.text, 'html.parser')

    # Get the names for all of the cities and put them into a list
    lstcities = page_html.find(id = 'content')
    list(lstcities.children)
    lstref = list(lstcities.children)[7]
    list(lstref.children)

    # Create list with all html links for each city
    for link in lstref.find_all('a'):
        links.append(link.get('href'))

for citylink in links:
    # Make a get request
    cityresponse = rq.get('http://www.city-data.com/crime/' + citylink)
    # Sleep for a random time between loops so website does not get spammed
    time.sleep(random.randint(8,15))

    # Get the html for the city and find the crime data we want (types of
    # crime, crime per 100k people, crime index)
    crimesoup = bsoup(cityresponse.text, 'html.parser')
    crimehtml = list(crimesoup.children)[2]
    crimebody = list(crimehtml.children)[3]
    crimeol = list(crimebody.children)[9]
    crimeli = list(crimeol.children)[9]

    # Get city and state name
    citystate = crimeli.get_text()
    citystate = citystate.split(',')
    citya = citystate[0]
    currcity = citya.replace('Crime rate in ', '')
    city.append(currcity)
    statea = citystate[1]
    stateb = statea.split('(')
    state.append(stateb[0].strip())

    # Find the crime table
    table = crimesoup.find(id="crimeTab")
    b = list(table.children)[5]

    # Find murder numbers
    murd = list(b.children)[1]
```

```python
c = 0
for i in list(murd.children):
    c = c+1
murdnum = list(murd.children)[c-1]

# Find numbers for total murders in 2017 and murders per 100,000 people
d = 0
for j in list(murdnum.children):
    d = d+1
if (d == 1):
    murders.append(float('NaN'))
    murdersper.append(float('NaN'))
else:
    murdtotal = int(list(murdnum.children)[0].replace(',', ''))
    murdper = list(list(murdnum.children)[2])[0]
    murdper = murdper[1:]
    murdper = float(murdper[:-1].replace(',', ''))
    murders.append(murdtotal)
    murdersper.append(murdper)

# Get rape numbers
ra = list(b.children)[3]
ranum = list(ra.children)[c-1]
d = 0
for j in list(ranum.children):
    d = d+1
if (d == 1):
    rapes.append(float('NaN'))
    rapesper.append(float('NaN'))
else:
    # Get numbers for total rapes in 2017 and rapes per 100,000 people
    ratotal = int(list(ranum.children)[0].replace(',', ''))
    raper = list(list(ranum.children)[2])[0]
    raper = raper[1:]
    raper = float(raper[:-1].replace(',', ''))
    rapes.append(ratotal)
    rapesper.append(raper)

# Get robbery numbers
rob = list(b.children)[5]
robnum = list(rob.children)[c-1]

d = 0
for j in list(robnum.children):
    d = d+1
if (d == 1):
    robberies.append(float('NaN'))
    robberiesper.append(float('NaN'))
```

```
else:
    # Get numbers for total robberies in 2017 and robberies per 100,000 people
    robtotal = int(list(robnum.children)[0].replace(',', ''))
    robper = list(list(robnum.children)[2])[0]
    robper = robper[1:]
    robper = float(robper[:-1].replace(',', ''))
    robberies.append(robtotal)
    robberiesper.append(robper)

# Get assault numbers
assau = list(b.children)[7]
assaunum = list(assau.children)[c-1]
d = 0
for j in list(assaunum.children):
    d = d+1
if (d == 1):
    assaults.append(float('NaN'))
    assaultsper.append(float('NaN'))
else:
    # Get numbers for total assaults in 2017 and assaults per 100,000 people
    assautotal = int(list(assaunum.children)[0].replace(',', ''))
    assauper = list(list(assaunum.children)[2])[0]
    assauper = assauper[1:]
    assauper = float(assauper[:-1].replace(',', ''))
    assaults.append(assautotal)
    assaultsper.append(assauper)

# Get burlgary numbers
bur = list(b.children)[9]
burgnum = list(bur.children)[c-1]
d = 0
for j in list(burgnum.children):
    d = d+1
if (d == 1):
    burglaries.append(float('NaN'))
    burglariesper.append(float('NaN'))
else:
    # Get numbers for total burglaries in 2017 and burglaries per 100,000 people
    burgtotal = int(list(burgnum.children)[0].replace(',', ''))
    burgper = list(list(burgnum.children)[2])[0]
    burgper = burgper[1:]
    burgper = float(burgper[:-1].replace(',', ''))
    burglaries.append(burgtotal)
    burglariesper.append(burgper)

# Get theft numbers
thef = list(b.children)[11]
theftnum = list(thef.children)[c-1]
```

```
d = 0
for j in list(theftnum.children):
    d = d+1
if (d == 1):
    thefts.append(float('NaN'))
    theftsper.append(float('NaN'))
else:
    # Get numbers for total thefts in 2017 and thefts per 100,000 people
    thefttotal = int(list(theftnum.children)[0].replace(',', ''))
    theftper = list(list(theftnum.children)[2])[0]
    theftper = theftper[1:]
    theftper = float(theftper[:-1].replace(',', ''))
    thefts.append(thefttotal)
    theftsper.append(theftper)

# Get auto theft numbers
authef = list(b.children)[13]
autotheftnum = list(authef.children)[c-1]
d = 0
for j in list(autotheftnum.children):
    d = d+1
if (d == 1):
    auto_thefts.append(float('NaN'))
    auto_theftsper.append(float('NaN'))
else:
    # Get numbers for total auto thefts in 2017 and auto thefts per 100,000 people
    autothefttotal = int(list(autotheftnum.children)[0].replace(',', ''))
    autotheftper = list(list(autotheftnum.children)[2])[0]
    autotheftper = autotheftper[1:]
    autotheftper = float(autotheftper[:-1].replace(',', ''))
    auto_thefts.append(autothefttotal)
    auto_theftsper.append(autotheftper)

# Get arson numbers
ar = list(b.children)[15]
arsonnum = list(ar.children)[c-1]
d = 0
for j in list(arsonnum.children):
    d = d+1
if (d == 1):
    arsons.append(float('NaN'))
    arsonsper.append(float('NaN'))
else:
    # Get numbers for total arsons in 2017 and arsons per 100,000 people
    arsontotal = int(list(arsonnum.children)[0].replace(',', ''))
    arsonper = list(list(arsonnum.children)[2])[0]
    arsonper = arsonper[1:]
    arsonper = float(arsonper[:-1].replace(',', ''))
```

```
            arsons.append(arsontotal)
            arsonsper.append(arsonper)

        # Get crime index numbers
        cind = list(b.children)[17]
        cindnum = list(cind.children)[0]
        d = 0
        for j in list(cindnum.children):
            d = d+1
        crate = list(cindnum.children)[d-1]
        crimeind = float(list(crate.children)[0])
        crime_index.append(crimeind)

# Create a dataframe with all of the crime data collected
crime = pd.DataFrame({
        'city': city,
        'state': state,
        'murders': murders,
        'murdersper100k': murdersper,
        'rapes': rapes,
        'rapesper100k': rapesper,
        'robberies': robberies,
        'robberiesper100k': robberiesper,
        'assaults': assaults,
        'assaultsper100k': assaultsper,
        'burglaries': burglaries,
        'burglariesper100k': burglariesper,
        'thefts': thefts,
        'theftsper100k': theftsper,
        'autothefts': auto_thefts,
        'autotheftsper100k': auto_theftsper,
        'arson': arsons,
        'arsonper100k': arsonsper,
        'crime index': crime_index
    })
crime

# Export the crime dataframe as a csv file
crime.to_csv('crime_scrapingmultstates4.csv')
```

6.0.4 Gini Index Dataset

- Dataset Name: city_gini_index.csv
- Link to the dataset: https://tinyurl.com/yxtoebgb
- Number of observations: 3573

The Gini Index Dataset was downloaded from American Fact Finder which allows users to search data colleted by the United States Census Bureau. The data is from the 2017 American

Community Survey and it has 3573 cities with their ID, location, estimated Gini Index, and margin of error. The Gini Index dataset is used as supporting data to the household income dataset.

7 Setup

```
In [1]: # Import libraries
        import re
        import sys
        import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        import sklearn
        import patsy
        import statsmodels.api as sm
        import scipy.stats as stats
        from scipy.stats import ttest_ind, chisquare, normaltest
        from sklearn import preprocessing

        # Don't display too many rows/cols of DataFrames
        pd.options.display.max_rows = 7
        pd.options.display.max_columns = 10
```

8 Data Cleaning

```
In [2]: # Load crime data
        df_crime = pd.read_csv('UScrime_scraped.csv')
        # Drop unnecessary extra index column
        df_crime.drop(columns = ['Unnamed: 0'], inplace = True)
        df_crime
```

```
Out[2]:              city    state  murders  murdersper100k  rapes     ...       \
        0       Abbeville  Alabama      0.0             0.0    2.0     ...
        1      Adamsville  Alabama      1.0            23.1    1.0     ...
        2         Addison  Alabama      0.0             0.0    0.0     ...
        ...           ...      ...      ...             ...    ...     ...
        9862   Torrington  Wyoming      0.0             0.0    0.0     ...
        9863    Wheatland  Wyoming      0.0             0.0    0.0     ...
        9864      Worland  Wyoming      0.0             0.0    2.0     ...

               autothefts  autotheftsper100k  arson  arsonper100k  crime index
        0             6.0              231.7    NaN           NaN        265.3
        1            15.0              346.1    NaN           NaN        468.4
        2             2.0              271.0    NaN           NaN        117.9
        ...           ...                ...    ...           ...          ...
        9862          3.0               44.6    0.0           0.0         91.5
        9863          7.0              194.3    0.0           0.0        117.2
```

```
9864          3.0                  56.7     0.0            0.0         118.4

[9865 rows x 19 columns]
```

First, let's look at the income data

```
In [3]: # Load income data
        df_income = pd.read_csv('economic_data.csv')
        # Drop unnecessary extra index column
        df_income.drop(columns = ['Unnamed: 0'], inplace = True)
        df_income
```

```
Out[3]:                                                      place percentile  \
        0      https://statisticalatlas.com/place/Alabama/Ala...       95th
        1      https://statisticalatlas.com/place/Alabama/Ala...       80th
        2      https://statisticalatlas.com/place/Alabama/Ala...       60th
        ...                                                  ...        ...
        10869  https://statisticalatlas.com/place/Wyoming/Pow...     Median
        10870  https://statisticalatlas.com/place/Wyoming/Pow...       40th
        10871  https://statisticalatlas.com/place/Wyoming/Pow...       20th

                                           income                     percent
        0      0    177,359.000000\rdtype: object  0    241.881\rdtype: object
        1      0    122,176.000000\rdtype: object  0    166.623\rdtype: object
        2       0    85,277.000000\rdtype: object  0    116.300\rdtype: object
        ...                                   ...                         ...
        10869   0    46,971.000000\rdtype: object  0    100.000\rdtype: object
        10870   0    40,583.000000\rdtype: object   0    86.400\rdtype: object
        10871   0    23,336.000000\rdtype: object   0    49.682\rdtype: object

        [10872 rows x 4 columns]
```

After loading the crime data and the income data, it was necessary for us to extract the city and state within the url in the place column of our income df. Then we reordered the columns, and cleaned up the dataframe to match up with the city and state columns in our crime data's csv.

```
In [4]: # Extract city and state from url
        df_income['citystate'] = df_income['place'].str.extract("place/(.*)/")
        # Extract state
        df_income['state'] = df_income['citystate'].str.extract("(.*)/")
        # Extract city
        df_income['city'] = df_income['citystate'].str.extract("/(.*)")
        # Remove place and citystate columns
        df_income = df_income.drop(['place', 'citystate'], axis=1)
        # Reorder columns
        df_income = df_income[['city', 'state', 'percentile', 'income', 'percent']]
        # Remove zeroes in income and percent columns
        df_income['income'] = df_income['income'].replace({'0 ':''}, regex = True)
        df_income['percent'] = df_income['percent'].replace({'0 ':''}, regex = True)
        df_income
```

```
Out[4]:             city    state percentile                                   income  \
        0      Alabaster  Alabama       95th     177,359.000000\rdtype: object
        1      Alabaster  Alabama       80th     122,176.000000\rdtype: object
        2      Alabaster  Alabama       60th      85,277.000000\rdtype: object
        ...          ...      ...        ...                                 ...
        10869     Powell  Wyoming     Median      46,971.000000\rdtype: object
        10870     Powell  Wyoming       40th      40,583.000000\rdtype: object
        10871     Powell  Wyoming       20th      23,336.000000\rdtype: object

                                  percent
        0         241.881\rdtype: object
        1         166.623\rdtype: object
        2         116.300\rdtype: object
        ...                           ...
        10869     100.000\rdtype: object
        10870      86.400\rdtype: object
        10871      49.682\rdtype: object

        [10872 rows x 5 columns]
```

Then, the income column & percentile column are cleaned up to be changed into ints, so we could pivot the data, making each percentile (20th, 40th, etc.) into a column and organizing our data more aesthetically and usefully.

```
In [5]: # Convert income to int
        pd.options.mode.chained_assignment = None
        for i in range(0, len(df_income)):
            incomeConvert = df_income['income'][i]
            incomeConvert = incomeConvert[:(incomeConvert.find("."))]
            incomeConvert = incomeConvert.replace(',', "")
            incomeConvert = re.sub(r"^\s+", "", incomeConvert, flags=re.UNICODE)

            incomeConvert = int(float(incomeConvert))
            df_income['income'][i] = incomeConvert

        # Drop 'percent' column
        # Make percentile columns 20th, 40th, Median, 60th, 80th, 95th
        df_percentile = df_income.pivot_table(index=["state","city"],
                                              columns='percentile',
                                              values=['income'], aggfunc='first')
        df_percentile.columns = df_percentile.columns.droplevel()
        df_percentile = df_percentile.reset_index()
        df_percentile.columns=df_percentile.columns.tolist()
        df_percentile = df_percentile[['city','state','20th','40th','Median',
                                       '60th','80th','95th']]
        df_percentile
```

```
Out[5]:                 city    state   20th   40th  Median   60th    80th    95th
        0          Alabaster  Alabama  33578  61734   73325  85277  122176  177359
```

```
1         Albertville   Alabama  17270  27280   32042  43119   73798  128375
2     Alexander-City   Alabama  13295  23247   30442  38488   65625  133750
...              ...       ...    ...    ...     ...    ...     ...     ...
1567        Sheridan   Wyoming  20786  37456   48804  61526   95356  152329
1568      Torrington   Wyoming  18806  36662   41959  50048   86015  154477
1569         Worland   Wyoming  20148  32634   39904  52766   80107  165486

[1570 rows x 8 columns]
```

In [6]:
```python
# Create inequality column: 95th minus 20th
inequality = [0]*len(df_percentile)
for i in range(0,len(df_percentile)):
    inequality[i] = df_percentile['95th'][i] - df_percentile['20th'][i]

df_percentile['income inequality'] = inequality
df_percentile
```

Out[6]:
```
                city    state   20th   40th  Median   60th    80th    95th  \
0          Alabaster  Alabama  33578  61734   73325  85277  122176  177359
1        Albertville  Alabama  17270  27280   32042  43119   73798  128375
2     Alexander-City  Alabama  13295  23247   30442  38488   65625  133750
...              ...      ...    ...    ...     ...    ...     ...     ...
1567        Sheridan  Wyoming  20786  37456   48804  61526   95356  152329
1568      Torrington  Wyoming  18806  36662   41959  50048   86015  154477
1569         Worland  Wyoming  20148  32634   39904  52766   80107  165486

      income inequality
0                143781
1                111105
2                120455
...                 ...
1567             131543
1568             135671
1569             145338

[1570 rows x 9 columns]
```

After cleaning the data, we could then merge the two dataframes using the city and state columns that appeared in both.

In [7]:
```python
crime_income_df = pd.merge(df_percentile, df_crime, on=['city','state'])
crime_income_df
```

Out[7]:
```
             city    state   20th   40th  Median  ...        autothefts  \
0       Alabaster  Alabama  33578  61734   73325  ...              21.0
1     Albertville  Alabama  17270  27280   32042  ...              90.0
2        Anniston  Alabama  12553  22337   30539  ...             110.0
..            ...      ...    ...    ...     ...  ...               ...
921      Sheridan  Wyoming  20786  37456   48804  ...              20.0
```

```
922   Torrington  Wyoming  18806  36662   41959     ...              3.0
923      Worland  Wyoming  20148  32634   39904     ...              3.0

     autotheftsper100k  arson  arsonper100k  crime index
0                 63.2    NaN           NaN        115.9
1                416.9    NaN           NaN        200.0
2                501.0    NaN           NaN       1302.8
..                 ...    ...           ...          ...
921              110.9    2.0          11.1        101.1
922               44.6    0.0           0.0         91.5
923               56.7    0.0           0.0        118.4

[924 rows x 26 columns]
```

Now we want to add in quintile ratios to get a better measure of income inequality. This index of inequality will be the 80th percentile's value divided by the 20th percentile's value. This is known as the Quintile Share, and according to the worldbank, the EU uses this to monitor income distribution in countries.

There's more information about it here: https://siteresources.worldbank.org/PGLP/Resources/inequality_m qeD3KhvjHAaP3jcW4_Qk5Ph0Oaekc88xAg.

In [8]:
```
# Zipping the quintiles together so they're easy to digest in a function.
quintile_values = list(zip(list(crime_income_df['20th']),
                           list(crime_income_df['80th'])))
# iterate through the tuples, creating the quintile share.
# Then, appending that to a list, which will become our quintile ratio column.
quintile_share = []
for i in range(len(quintile_values)):
    val = quintile_values[i][1] / quintile_values[i][0]
    quintile_share.append(val)
crime_income_df["quintile share"] = pd.Series(quintile_share)

crime_income_df.head()
```

Out[8]:
```
          city    state   20th   40th  Median       ...        \
0    Alabaster  Alabama  33578  61734   73325       ...
1  Albertville  Alabama  17270  27280   32042       ...
2     Anniston  Alabama  12553  22337   30539       ...
3       Athens  Alabama  16777  33804   45920       ...
4       Auburn  Alabama  10718  26433   38912       ...

   autotheftsper100k  arson  arsonper100k  crime index  quintile share
0               63.2    NaN           NaN        115.9        3.638573
1              416.9    NaN           NaN        200.0        4.273191
2              501.0    NaN           NaN       1302.8        5.215646
3               46.1    NaN           NaN        140.2        6.247660
4              155.8    NaN           NaN        217.4        9.969491

[5 rows x 27 columns]
```

Now we want to look at the Gini index data.

```
In [9]: # Import city gini index data
        gini_index_df = pd.read_csv('city_gini_index.csv', encoding='latin-1', header = 1)
        # Drop the two ID columns which will not be used
        gini_index_df = gini_index_df.drop(columns = ['Id', 'Id2'])
        gini_index_df
```

```
Out[9]:                                  Geography  Estimate; Gini Index  \
        0       Abbeville, LA Urban Cluster (2010)                0.4608
        1       Abbeville, SC Urban Cluster (2010)                0.5020
        2      Abbotsford, WI Urban Cluster (2010)                0.4354
        ...                                    ...                   ...
        3570    Zimmerman, MN Urban Cluster (2010)                0.3583
        3571     Zumbrota, MN Urban Cluster (2010)                0.4219
        3572  Zuni Pueblo, NM Urban Cluster (2010)                0.4493

              Margin of Error; Gini Index
        0                          0.0214
        1                          0.0415
        2                          0.0507
        ...                           ...
        3570                       0.0465
        3571                       0.0342
        3572                       0.0465

        [3573 rows x 3 columns]
```

First we want to separate the values in the Geography column into a city and state column so we can merge it easily with the crime dataframe. Then we want to convert the abbreviation for each state into it's full name so it is in the same format as the crime dataframe state column.

```
In [10]: # Create empty arrays for new columns city and state
         city = []
         state = []
         # Loop through the gini index dataframe and convert the
         # state name to its abbreviation
         for citystate in gini_index_df.iterrows():
             strcity = str(citystate[1][0])

             # Get the city and state name
             cityname = strcity.split(',')[0].strip()
             splitcity = cityname.split('--')
             if (len(splitcity) > 1):
                 cityname = splitcity[1]
             else:
                 cityname = splitcity[0]
             statename = strcity.split(',')[1].strip()
             newstate = statename.split(' ')[0].strip()
```

```
    city.append(cityname)
    state.append(newstate)

# Drop the old geography column and add the city and state columns
gini_index_df['city'] = city
gini_index_df['state'] = state
gini_index_df.drop(columns = ['Geography'], inplace = True)

# Dictionary used to convert the state name to its abbreviation
us_state_abbrev = {
    'AL': 'Alabama',
    'AK': 'Alaska',
    'AZ': 'Arizona',
    'AR': 'Arkansas',
    'CA': 'California',
    'CO': 'Colorado',
    'CT': 'Connecticut',
    'DE': 'Delaware',
    'FL': 'Florida',
    'GA': 'Georgia',
    'HI': 'Hawaii',
    'ID': 'Idaho',
    'IL': 'Illinois',
    'IN': 'Indiana',
    'IA': 'Iowa',
    'KS': 'Kansas',
    'KY': 'Kentucky',
    'LA': 'Louisiana',
    'ME': 'Maine',
    'MD': 'Maryland',
    'MA': 'Massachusetts',
    'MI': 'Michigan',
    'MN': 'Minnesota',
    'MS': 'Mississippi',
    'MO': 'Missouri',
    'MT': 'Montana',
    'NE': 'Nebraska',
    'NV': 'Nevada',
    'NH': 'New Hampshire',
    'NJ': 'New Jersey',
    'NM': 'New Mexico',
    'NY': 'New York',
    'NC': 'North Carolina',
    'ND': 'North Dakota',
    'OH': 'Ohio',
    'OK': 'Oklahoma',
    'OR': 'Oregon',
    'PA': 'Pennsylvania',
```

```
    'RI': 'Rhode Island',
    'SC': 'South Carolina',
    'SD': 'South Dakota',
    'TN': 'Tennessee',
    'TX': 'Texas',
    'UT': 'Utah',
    'VT': 'Vermont',
    'VA': 'Virginia',
    'WA': 'Washington',
    'WV': 'West Virginia',
    'WI': 'Wisconsin',
    'WY': 'Wyoming',
    'DC': 'District of Columbia'
}

newcol = []
# Loop through the gini index dataframe and convert
# the state name to its abbreviation
for strstate in gini_index_df.iterrows():
    # Get the state name abbreviation
    currstate = str(strstate[1][3]).split('--')
    if (len(currstate) > 1):
        currstate = currstate[1]
    else:
        currstate = currstate[0]
    currstate = currstate.strip()

    # Search through the dictionary for the abbreviation and
    # change it to the full state name
    for stateabbrev, state in us_state_abbrev.items():
        if currstate == stateabbrev:
            newcol.append(state)

# Replace the old state column with the long form state column
gini_index_df['state'] = newcol
gini_index_df
```

Out[10]:

```
      Estimate; Gini Index  Margin of Error; Gini Index         city  \
0                   0.4608                       0.0214    Abbeville
1                   0.5020                       0.0415    Abbeville
2                   0.4354                       0.0507   Abbotsford
...                    ...                          ...          ...
3570                0.3583                       0.0465    Zimmerman
3571                0.4219                       0.0342     Zumbrota
3572                0.4493                       0.0465  Zuni Pueblo

                state
0           Louisiana
```

```
1       South Carolina
2            Wisconsin
...                ...
3570         Minnesota
3571         Minnesota
3572        New Mexico

[3573 rows x 4 columns]
```

Now we want to remove any outliers by their Gini index and crime index to make sure that analysis is not weighting them in our analysis.

In [11]:
```
# Remove Gini index outliers based on 3 standard
# deviations from the mean and z score
outliersgini=[]
indexesgini = []
threshold=3
mean_gini = np.mean(gini_index_df['Estimate; Gini Index'])
std_gini =np.std(gini_index_df['Estimate; Gini Index'])

for i in gini_index_df.iterrows():
    gini = i[1][0]
    indexgini = i[0]
    z_scoregini= (gini - mean_gini)/std_gini
    if np.abs(z_scoregini) > threshold:
        outliersgini.append(gini)
        indexesgini.append(indexgini)

# Drop the outliers from the dataframe
gini_index_df.drop(index=indexesgini, inplace = True)
gini_index_df.shape

# Do the same for the crime index values
outliers=[]
indexes = []
threshold=3
mean_1 = np.mean(df_crime['crime index'])
std_1 =np.std(df_crime['crime index'])

for i in df_crime.iterrows():
    crime = i[1][18]
    index = i[0]
    z_score= (crime - mean_1)/std_1
    if np.abs(z_score) > threshold:
        outliers.append(crime)
        indexes.append(index)

df_crime.drop(index=indexes, inplace = True)
df_crime
```

```
Out[11]:             city    state  murders  murdersper100k  rapes     ...       \
        0      Abbeville  Alabama      0.0             0.0    2.0     ...
        1     Adamsville  Alabama      1.0            23.1    1.0     ...
        2        Addison  Alabama      0.0             0.0    0.0     ...
        ...          ...      ...      ...             ...    ...     ...
        9862  Torrington  Wyoming      0.0             0.0    0.0     ...
        9863   Wheatland  Wyoming      0.0             0.0    0.0     ...
        9864     Worland  Wyoming      0.0             0.0    2.0     ...

              autothefts  autotheftsper100k  arson  arsonper100k  crime index
        0            6.0              231.7    NaN           NaN        265.3
        1           15.0              346.1    NaN           NaN        468.4
        2            2.0              271.0    NaN           NaN        117.9
        ...          ...                ...    ...           ...          ...
        9862         3.0               44.6    0.0           0.0         91.5
        9863         7.0              194.3    0.0           0.0        117.2
        9864         3.0               56.7    0.0           0.0        118.4

        [9756 rows x 19 columns]
```

```
In [12]: # Merge gini index dataframe with crime dataframe using the county_name columns
         crime_gini_df = pd.merge(gini_index_df, df_crime, on=['city', 'state'])
         crime_gini_df.shape
```

```
Out[12]: (2768, 21)
```

At the end of our data cleaning, we now now two datasets to analyze: crime_income_df and crime_gini_df. By looking at these two metrics of income inequality we can see if the results from both data sets differ or concur with our hypothesis. This will gives a better idea of how certain we are about our hypothesis or possible inconsistencies in how we define income inequality and crime in a city.

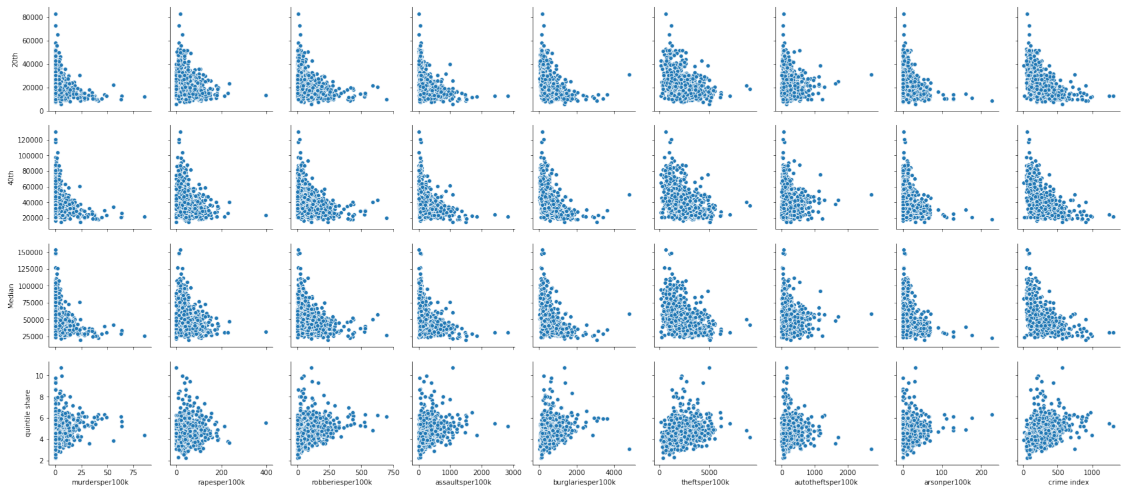
9 Data Analysis & Results

9.0.1 Quintile Share and Crime Analysis

We are first going to look at how quintile share, one type of way to measure income inequality, relates to crime. Let's take a quick look at the the crime and quintile share data we have by creating a pairplot.

```
In [13]: # Create a pair plot with income columns and crime per 100,000 based on population
         sns.pairplot(crime_income_df, y_vars = ['20th', '40th', 'Median',
                                                  'quintile share'],
                      x_vars = ['murdersper100k', 'rapesper100k', 'robberiesper100k',
                                'assaultsper100k', 'burglariesper100k', 'theftsper100k',
                                'autotheftsper100k', 'arsonper100k', 'crime index'])
```

```
Out[13]: <seaborn.axisgrid.PairGrid at 0x1c21c412e8>
```



Visually speaking, it seems very clear that poverty connects with crime. Places with wealthier 20th percentiles have low crime, and places with poorer 20th percentiles have more crime. The same is true of the median and 40th percentiles. The relationship with the quintile share seems a little more complicated. Recall that a higher quintile share indicates a higher level of inequality. There seems to be a soft trend where the quintile share does relate to level of crime, but it is by no means a stark one.

An interesting observation is that the quintile share (as well as 20th, 40th and median percentile levels) all seem to correlate with different kinds of crimes in the same way. They seem to correlate with all sorts of crime across the board, rather than with just one or two distinct kinds.

Let's look closer at how quintile share relates to specific types of crimes per 100,000 population.

In [14]:
```
# Section out quintile share and specific crimes per 100,000 population
df_crimeper100 = crime_income_df[['quintile share', 'murdersper100k',
                                  'rapesper100k', 'robberiesper100k',
                                  'assaultsper100k','burglariesper100k',
                                  'theftsper100k', 'autotheftsper100k',
                                  'arsonper100k', 'crime index']]
# Create a table with their correlation
corrs_crimeper100 = df_crimeper100.corr()
corrs_crimeper100
```

Out[14]:
```
                   quintile share  murdersper100k  rapesper100k  \
quintile share           1.000000        0.263979      0.135648
murdersper100k           0.263979        1.000000      0.170459
rapesper100k             0.135648        0.170459      1.000000
...                           ...             ...           ...
autotheftsper100k        0.073394        0.310346      0.264664
arsonper100k             0.208815        0.386974      0.264512
crime index              0.359841        0.650385      0.531987

                   robberiesper100k  assaultsper100k  burglariesper100k  \
quintile share             0.341071         0.298336           0.315672
```

```
murdersper100k         0.606552        0.571986          0.505855
rapesper100k           0.269519        0.378451          0.278477
...                         ...             ...               ...
autotheftsper100k      0.564758        0.334505          0.464945
arsonper100k           0.377354        0.342515          0.397116
crime index            0.762285        0.830321          0.776285

                   theftsper100k  autotheftsper100k  arsonper100k  crime index
quintile share          0.288744           0.073394      0.208815     0.359841
murdersper100k          0.315939           0.310346      0.386974     0.650385
rapesper100k            0.278684           0.264664      0.264512     0.531987
...                          ...                ...           ...          ...
autotheftsper100k       0.456257           1.000000      0.296172     0.612149
arsonper100k            0.288854           0.296172      1.000000     0.464297
crime index             0.746923           0.612149      0.464297     1.000000

[10 rows x 10 columns]
```

There seems to be a fairly solid correlation between the crime index and the quintile share here; 0.35 is certainly less correlated than some of the other values we're seeing, but it makes sense that individual types of crime per 100k would be very strongly related with the crime index, since they more or less determine it.

Income inequality, as measured by the quintile share, seems to most strongly correlate with robberies and burglaries per 100k, which makes some intuitive sense.

We will now check crime index against different percentiles (specifically 20th, Median, and 95th) of income instead of against the quintile share. This will give us an idea of how poverty in and of itself contributes to the problem.

In [15]:
```
# Section out 20th percentile and specific crimes per 100,000 population
df_20thper100 = crime_income_df[['20th', 'murdersper100k', 'rapesper100k',
                                  'robberiesper100k', 'assaultsper100k',
                                  'burglariesper100k', 'theftsper100k',
                                  'autotheftsper100k', 'arsonper100k',
                                  'crime index']]
# Create a tablewith their correlation
corrs_20thper100 = df_20thper100.corr()
corrs_20thper100
```

Out[15]:
```
                       20th  murdersper100k  rapesper100k  robberiesper100k  \
20th               1.000000       -0.339197     -0.331618         -0.350650
murdersper100k    -0.339197        1.000000      0.170459          0.606552
rapesper100k      -0.331618        0.170459      1.000000          0.269519
...                     ...             ...           ...               ...
autotheftsper100k -0.173704        0.310346      0.264664          0.564758
arsonper100k      -0.294415        0.386974      0.264512          0.377354
crime index       -0.514839        0.650385      0.531987          0.762285

                   assaultsper100k  burglariesper100k  theftsper100k  \
```

```
20th                        -0.416062          -0.441973       -0.407847
murdersper100k               0.571986           0.505855        0.315939
rapesper100k                 0.378451           0.278477        0.278684
...                               ...                ...             ...
autotheftsper100k            0.334505           0.464945        0.456257
arsonper100k                 0.342515           0.397116        0.288854
crime index                  0.830321           0.776285        0.746923

                   autotheftsper100k  arsonper100k  crime index
20th                       -0.173704     -0.294415    -0.514839
murdersper100k              0.310346      0.386974     0.650385
rapesper100k                0.264664      0.264512     0.531987
...                              ...           ...          ...
autotheftsper100k           1.000000      0.296172     0.612149
arsonper100k                0.296172      1.000000     0.464297
crime index                 0.612149      0.464297     1.000000

[10 rows x 10 columns]
```

The negative correlation between the 20th percentile of income against crimes per 100k is a lot stronger than simply against counts of crime. Aside from autothefts at correlation -0.173704, all the other crimes have a correlation between -0.45 and -0.29 with income's 20th percentile.

In [16]:
```python
# Section out median income and specific crimes per 100,000 population
df_Medper100 = crime_income_df[['Median', 'murdersper100k', 'rapesper100k',
                                'robberiesper100k', 'assaultsper100k',
                                'burglariesper100k', 'theftsper100k',
                                'autotheftsper100k', 'arsonper100k',
                                'crime index']]
# Create a tablewith their correlation
corrs_Medper100 = df_Medper100.corr()
corrs_Medper100
```

Out[16]:
```
                     Median  murdersper100k  rapesper100k  robberiesper100k  \
Median             1.000000       -0.336887     -0.342925         -0.316938
murdersper100k    -0.336887        1.000000      0.170459          0.606552
rapesper100k      -0.342925        0.170459      1.000000          0.269519
...                     ...             ...           ...               ...
autotheftsper100k -0.177613        0.310346      0.264664          0.564758
arsonper100k      -0.286220        0.386974      0.264512          0.377354
crime index       -0.512659        0.650385      0.531987          0.762285

                   assaultsper100k  burglariesper100k  theftsper100k  \
Median                   -0.412161          -0.452121      -0.408438
murdersper100k            0.571986           0.505855       0.315939
rapesper100k              0.378451           0.278477       0.278684
...                            ...                ...            ...
autotheftsper100k         0.334505           0.464945       0.456257
```

```
arsonper100k                0.342515            0.397116       0.288854
crime index                 0.830321            0.776285       0.746923

                   autotheftsper100k  arsonper100k  crime index
Median                     -0.177613     -0.286220    -0.512659
mursdersper100k             0.310346      0.386974     0.650385
rapesper100k                0.264664      0.264512     0.531987
...                              ...           ...          ...
autotheftsper100k           1.000000      0.296172     0.612149
arsonper100k                0.296172      1.000000     0.464297
crime index                 0.612149      0.464297     1.000000

[10 rows x 10 columns]
```

Once again, similar to what we saw for the 20th percentile, for the Median, there is a stronger negative correlation between income and crime per 100k than between income and just counts of crime. Against crime index, the negative correlation is -0.512659.

```
In [17]: # Section out 95th percentile income and specific crimes per 100,000 population
         df_95thper100 = crime_income_df[['95th', 'murdersper100k', 'rapesper100k',
                                          'robberiesper100k', 'assaultsper100k',
                                     'burglariesper100k', 'theftsper100k',
                                          'autotheftsper100k', 'arsonper100k',
                                          'crime index']]
         # Create a tablewith their correlation
         corrs_95thper100 = df_95thper100.corr()
         corrs_95thper100
```

```
Out[17]:                        95th  murdersper100k  rapesper100k  robberiesper100k  \
         95th               1.000000       -0.240329     -0.302745         -0.130805
         murdersper100k    -0.240329        1.000000      0.170459          0.606552
         rapesper100k      -0.302745        0.170459      1.000000          0.269519
         ...                     ...             ...           ...               ...
         autotheftsper100k -0.091805        0.310346      0.264664          0.564758
         arsonper100k      -0.238494        0.386974      0.264512          0.377354
         crime index       -0.354678        0.650385      0.531987          0.762285

                            assaultsper100k  burglariesper100k  theftsper100k  \
         95th                     -0.302601          -0.342421      -0.257003
         murdersper100k            0.571986           0.505855       0.315939
         rapesper100k              0.378451           0.278477       0.278684
         ...                            ...                ...            ...
         autotheftsper100k         0.334505           0.464945       0.456257
         arsonper100k              0.342515           0.397116       0.288854
         crime index               0.830321           0.776285       0.746923

                            autotheftsper100k  arsonper100k  crime index
         95th                       -0.091805     -0.238494    -0.354678
```

```
murdersper100k              0.310346      0.386974      0.650385
rapesper100k                0.264664      0.264512      0.531987
...                              ...           ...           ...
autotheftsper100k           1.000000      0.296172      0.612149
arsonper100k                0.296172      1.000000      0.464297
crime index                 0.612149      0.464297      1.000000

[10 rows x 10 columns]
```

Correlation is negative once again though when we check income's 95th percentile against the crimes per 100k in the population. Against the crime index, we have a correlation of -0.354678.

As we have seen from these correlation tables, looking at just one percentile does not quite capture the idea of income inequality so we will be using the quintile share values which better takes into account the percent of income controlled by a certain portion of the population, not just the income of a percentile.

Now let's create a new column which categorizes each location as a place where there is high inequality (1) or low inequality (0). This will help determine if quintile share is an independently influencing factor on crime rates.

In [18]:
```python
# Create 'ineq_exists' column: '1' if exists, '0' if doesn't
# Income inequality defined as >= median of all income inequalities
income_ineq_median = crime_income_df["quintile share"].median()

ineq_exists = [0]*len(crime_income_df)
for i in range(0,len(crime_income_df)):
    if crime_income_df["quintile share"][i] >= income_ineq_median:
        ineq_exists[i] = 1
    else:
        ineq_exists[i] = 0
crime_income_df['inequality exists'] = ineq_exists
crime_income_df.head()
```

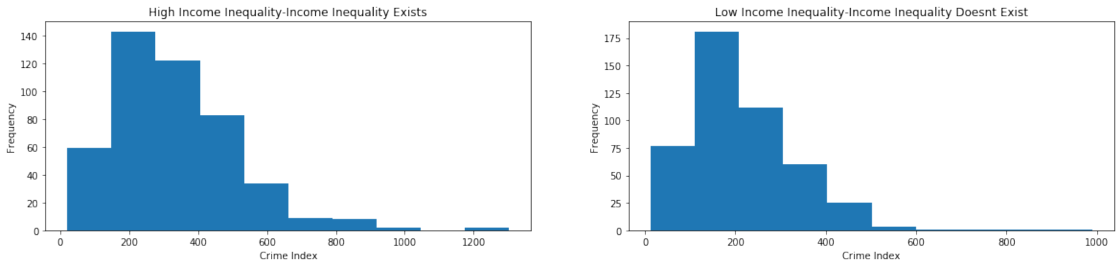
Out[18]:
```
          city    state   20th   40th  Median        ...         arson  \
0    Alabaster  Alabama  33578  61734   73325        ...           NaN
1  Albertville  Alabama  17270  27280   32042        ...           NaN
2     Anniston  Alabama  12553  22337   30539        ...           NaN
3       Athens  Alabama  16777  33804   45920        ...           NaN
4       Auburn  Alabama  10718  26433   38912        ...           NaN

   arsonper100k  crime index  quintile share  inequality exists
0           NaN        115.9        3.638573                  0
1           NaN        200.0        4.273191                  0
2           NaN       1302.8        5.215646                  1
3           NaN        140.2        6.247660                  1
4           NaN        217.4        9.969491                  1

[5 rows x 28 columns]
```

As we can see below, the distribution of crime index for the two groups of low and high income inequality are not normal so we must transform them inorder to run tests to check if there is a significant influnce income inequality has on crime.

We normalize the data by using the normalize funtion from sklearn and doing a cuberoot transformation.

In [19]:
```
# Side-by-side histogram plots of crime index in
# areas with and without income inequality
fig, axes = plt.subplots(1, 2)

crime_income_df[crime_income_df["inequality exists"] == 1]["crime index"].plot \
.hist(ax = axes[0],
      title = 'High Income Inequality-Income Inequality Exists')
crime_income_df[crime_income_df["inequality exists"] == 0]["crime index"].plot \
.hist(ax = axes[1],
      title = 'Low Income Inequality-Income Inequality Doesn''t Exist')
# Test if there is a normal distribution with a p test
crime_ineq = crime_income_df[crime_income_df["inequality exists"] == 1] \
["crime index"].values
crime_no_ineq = crime_income_df[crime_income_df["inequality exists"] == 0] \
["crime index"].values
st_ineq, p_ineq = normaltest(crime_ineq)
st_no_ineq, p_no_ineq = normaltest(crime_no_ineq)
axes[0].set_xlabel('Crime Index')
axes[1].set_xlabel('Crime Index')

fig.set_size_inches(20, 4)

is_n_ineq = bool(p_ineq > 0.01)
if is_n_ineq == True:
    print('The distribution of crime index for income inequality existing \
is approximately normal.')
else:
    print('The distribution of crime index for income inequality existing is \
not approximately normal.')

is_n_no_ineq = bool(p_no_ineq > 0.01)
if is_n_no_ineq == True:
    print('The distribution of crime index for income inequality not existing \
is approximately normal.')
else:
    print('The distribution of crime index for income inequality not existing \
is not approximately normal.')
```

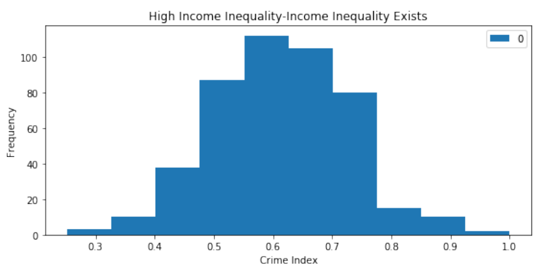
```
The distribution of crime index for income inequality existing is not approximately normal.
The distribution of crime index for income inequality not existing is not approximately normal.
```

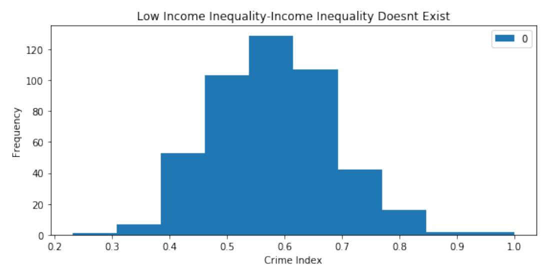



```
In [20]: # Normalizing and cube root
         crime_ineq = pd.Series(crime_ineq)
         crime_no_ineq = pd.Series(crime_no_ineq)

         crime_ineq =    pd.DataFrame(preprocessing.normalize([crime_ineq],norm='max'))
         crime_ineq = crime_ineq.transpose()
         crime_ineq = pd.DataFrame(np.cbrt(crime_ineq))

         crime_no_ineq = pd.DataFrame(preprocessing.normalize([crime_no_ineq],norm='max'))
         crime_no_ineq = crime_no_ineq.transpose()
         crime_no_ineq = pd.DataFrame(np.cbrt(crime_no_ineq))

         fig, axes = plt.subplots(1, 2)
         crime_ineq.plot.hist(ax = axes[0],
             title = 'High Income Inequality-Income Inequality Exists')
         crime_no_ineq.plot.hist(ax = axes[1],
             title = 'Low Income Inequality-Income Inequality Doesn''t Exist')
         axes[0].set_xlabel('Crime Index')
         axes[1].set_xlabel('Crime Index')

         fig.set_size_inches(20, 4)

         # Check for normality again
         st_ineq, p_ineq = normaltest(crime_ineq)
         st_no_ineq, p_no_ineq = normaltest(crime_no_ineq)

         is_n_ineq = bool(p_ineq > 0.01)
         if is_n_ineq == True:
             print('The distribution of crime index for income inequality \
         existing is approximately normal.')
         else:
             print('The distribution of crime index for income inequality \
         existing is not approximately normal.')

         is_n_no_ineq = bool(p_no_ineq > 0.01)
         if is_n_no_ineq == True:
             print('The distribution of crime index for income inequality \
```

```
not existing is approximately normal.')
else:
    print('The distribution of crime index for income inequality \
not existing is not approximately normal.')

print(p_ineq,p_no_ineq)
```

```
The distribution of crime index for income inequality existing is approximately normal.
The distribution of crime index for income inequality not existing is approximately normal.
[0.5475311] [0.03667113]
```





Success! Now that we have approximately normal distributions, we can do some more testing.

```
In [21]: # Check for significant difference
         t_val, p_val = ttest_ind(crime_ineq, crime_no_ineq)
         if p_val < 0.01:
             print('There is a significant difference.')
         else:
             print('There is NOT a significant difference.')
```

```
There is a significant difference.
```

After performing a 2-sample t-test, we can conclude that there is indeed a significant difference in crime index between areas where income inequality exists and areas where income inequality doesn't exist. But maybe this effect is due to a confound, namely poverty in and of itself so we should look at poverty values.

```
In [22]: # Create 'poverty_exists' column: '1' if exists, '0' if doesn't
         # poverty defined as 20th percentile income < mean of all 20th
         # percentile incomes
         mean20th = crime_income_df["20th"].mean()

         pov_exists = [0]*len(crime_income_df)
         for i in range(0,len(crime_income_df)):
             if crime_income_df["20th"][i] < mean20th:
                 pov_exists[i] = 0
```

```
        else:
            pov_exists[i] = 1
    crime_income_df['poverty exists'] = pov_exists
    print(len(crime_income_df[crime_income_df['poverty exists'] == 0]))
    print(len(crime_income_df[crime_income_df['poverty exists'] == 1]))
    crime_income_df.head()
```

```
561
363
```

```
Out[22]:          city    state   20th   40th  Median       ...       arsonper100k  \
         0   Alabaster  Alabama  33578  61734   73325       ...                NaN
         1 Albertville  Alabama  17270  27280   32042       ...                NaN
         2    Anniston  Alabama  12553  22337   30539       ...                NaN
         3      Athens  Alabama  16777  33804   45920       ...                NaN
         4      Auburn  Alabama  10718  26433   38912       ...                NaN

            crime index  quintile share  inequality exists  poverty exists
         0        115.9        3.638573                  0               1
         1        200.0        4.273191                  0               0
         2       1302.8        5.215646                  1               0
         3        140.2        6.247660                  1               0
         4        217.4        9.969491                  1               0

         [5 rows x 29 columns]
```

As we can see, based on our defintion of poverty, 561 cities do not experience poverty while 363 cities do.

Using `value_counts` from pandas, extract the number of 'poverty exists' and 'poverty doesn't exist', separately for 'income inequality exists' and 'income inequality doesn't exist'.

To do so:

- select from `crime_income_df` income inequality, 0 and 1 separately, extract the poverty exists column, and use the `value_counts` method.
- Save the counts for each 'poverty does/doesn't exist' for 'income inequality exists' to a variable called `pov_ineq`
- Save the counts for each 'poverty does/doesn't exist' for 'income inequality doesn't exist' to a variable called `pov_no_ineq`

```
In [23]: pov_ineq = crime_income_df[crime_income_df['inequality exists'] == 1] \
         ['poverty exists'].value_counts()
         pov_no_ineq = crime_income_df[crime_income_df['inequality exists'] == 0] \
         ['poverty exists'].value_counts()
         print(pov_ineq)
         print(pov_no_ineq)
```

```
0    409
1     53
```

```
Name: poverty exists, dtype: int64
1    310
0    152
Name: poverty exists, dtype: int64
```

What we saw from above is that of all the areas WITH income inequality, 409 cities do not experience poverty while 53 do. Meanwhile in all the areas WITHOUT income inequality, 310 cities DO experience poverty while 152 do not.

Let's find the ratio of poverty existing, the proportion of cities with poverty, in 'income inequality exists' and 'income inequality doesn't exist'. This will be value between 0.0 and 1.0, calculated as #(pov == 1) / (#(pov == 0) + #(pov == 1) - done separately for income inequality existing and not existing.

We will use the `pov_ineq` and `pov_no_ineq` variables to calculate these.

Save the ratio of poverty existing in 'inequality exists' to a variable `r_ineq`.

Save the ratio of poverty existing in 'inequality doesn't exist' to a variable `r_no_ineq`.

Note: keep these numbers as ratios (they should be decimal numbers, less than 1).

```
In [24]: r_ineq = pov_ineq[1]/(pov_ineq[0] + pov_ineq[1])
         r_no_ineq = pov_no_ineq[1]/(pov_no_ineq[0] + pov_no_ineq[1])

         print(r_ineq)
         print(r_no_ineq)
```

```
0.11471861471861472
0.670995670995671
```

The ratio of poverty existing in the two categories appear very different, but we will use a chi-squared test to see whether the difference in poverty-ratio between 'income inequality does/doesn't exist' is significantly different.

```
In [25]: chisq, p_val_chi = stats.chisquare(np.array([pov_ineq.values,
                                                      pov_no_ineq.values]), axis=None)


         if p_val_chi < 0.01:
             print('There is a significant difference in ratios!')
```

```
There is a significant difference in ratios!
```

We will now take a look at these comparisons in pivot tables.

We'll use the pandas `pivot_table` method to create pivot table and assign it to a variable `pv`.

We'll set the values as 'crime index', and the indices as 'poverty exists' and 'inequality exists' in the pivot table.

```
In [26]: pv = pd.pivot_table(crime_income_df, values='crime index', index=[ \
         'poverty exists', 'inequality exists'])
         pv
```

```
Out[26]:                                    crime index
         poverty exists inequality exists
         0              0                    276.013158
                        1                    352.225672
         1              0                    186.009032
                        1                    181.984906
```

Short recap: - Our initial hypothesis suggested there is a significant difference between crime index of counties with and without income inequality. - However, further analyses suggested there may be a confounding variable, as there is also a significantly different poverty balance between cities with and without income inequality.

Checking the average crime index, per 'inequality exists', split up by 'poverty exists', suggests there may not be a difference between 'inequality exists', other than what is explained by 'poverty exists'.

Now we want to statistically ask this question: is there still a difference in crime index between 'inequality exists', when controlling for differences in 'poverty exists'?

We will need to make some linear models, using Ordinary Least Squares (OLS).

We will do this using the method that is outlined in the 'LinearModels' Tutorial, using patsy, and statsmodels. - Create design matrices with `patsy.dmatrices` - Iniliaize an OLS model with `sm.OLS` - Fit the OLS model - Check the summary for results.

First let's only look at quintile share inequality and crime index and based on the model we create (using alpha value of 0.01), check if income inequality significantly predicts crime index.

```
In [27]: # rename some columns so that dmatrices() function can be used in next step
         crime_income_df.rename(columns={'crime index':'crimeindex',
                                         'inequality exists':'inequalityexists',
                                         'poverty exists':'povertyexists',
                                          'quintile share':'quintileshare'},
                                         inplace=True)

         # First look at how quintile share inequality affects crime index
         outcome_1, predictors_1 = patsy.dmatrices('crimeindex ~ inequalityexists',
                                                   crime_income_df)
         mod_1 = sm.OLS(outcome_1, predictors_1)
         res_1 = mod_1.fit()

         lm_1 = bool(res_1.pvalues[1] < 0.01)
         if lm_1 == True:
             print("Income inequality significantly predicts crime index.\n")
         else:
             print("Income inequality doesn't significantly predict crime index.\n")

         print(res_1.summary())
```

```
Income inequality significantly predicts crime index.

                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:            crimeindex   R-squared:                       0.126
Model:                           OLS   Adj. R-squared:                  0.125
Method:                Least Squares   F-statistic:                     133.0
Date:               Wed, 12 Jun 2019   Prob (F-statistic):           7.81e-29
Time:                       23:24:56   Log-Likelihood:                -5966.1
No. Observations:                924   AIC:                         1.194e+04
Df Residuals:                    922   BIC:                         1.195e+04
Df Model:                          1
Covariance Type:           nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
Intercept         215.6208      7.179     30.035      0.000     201.532     229.710
inequalityexists  117.0751     10.153     11.531      0.000      97.150     137.000
==============================================================================
Omnibus:                     292.501   Durbin-Watson:                   1.614
Prob(Omnibus):                 0.000   Jarque-Bera (JB):             1135.375
Skew:                          1.463   Prob(JB):                    2.86e-247
Kurtosis:                      7.574   Cond. No.                         2.62
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Now let's look at how both poverty and quintile share inequality affect crime index. Then check if it is a significant prediction based on the same alpha value of 0.01.

```
In [28]: # Look at how quintile share inequality and poverty affects crime index
         outcome_2, predictors_2 = patsy.dmatrices('crimeindex ~ inequalityexists \
                                                  + povertyexists', crime_income_df)
         mod_2 = sm.OLS(outcome_2, predictors_2)
         res_2 = mod_2.fit()

         lm_2 = bool(res_1.pvalues[1] < 0.01)
         if lm_1 == True:
             print("Income inequality significantly predicts crime index.\n")
         else:
             print("Income inequality doesn't significantly predict crime index.\n")

         print(res_2.summary())
```

```
Income inequality significantly predicts crime index.

                            OLS Regression Results
==============================================================================
Dep. Variable:            crimeindex   R-squared:                       0.205
Model:                           OLS   Adj. R-squared:                  0.203
```

```
Method:                 Least Squares   F-statistic:                     118.6
Date:                Wed, 12 Jun 2019   Prob (F-statistic):           1.45e-46
Time:                        23:24:56   Log-Likelihood:                -5922.4
No. Observations:                 924   AIC:                         1.185e+04
Df Residuals:                     921   BIC:                         1.187e+04
Df Model:                           2
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept           292.9769     10.607     27.620      0.000     272.159     313.794
inequalityexists     52.9444     11.788      4.491      0.000      29.810      76.079
povertyexists      -115.2856     12.068     -9.553      0.000    -138.970     -91.601
==============================================================================
Omnibus:                      312.565   Durbin-Watson:                   1.612
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1384.544
Skew:                           1.522   Prob(JB):                    2.24e-301
Kurtosis:                       8.167   Cond. No.                         4.42
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [29]:
```
ans = (lm_1 == True and lm_2 == True)
if ans == True:
    print("Cities with income inequality and cities without income \n \
inequality have a systematically different crime index.")
else:
    print("Cities with income inequality and cities without income \n \
inequality don't have a systematically different crime index.")
```

```
Cities with income inequality and cities without income
 inequality have a systematically different crime index.
```

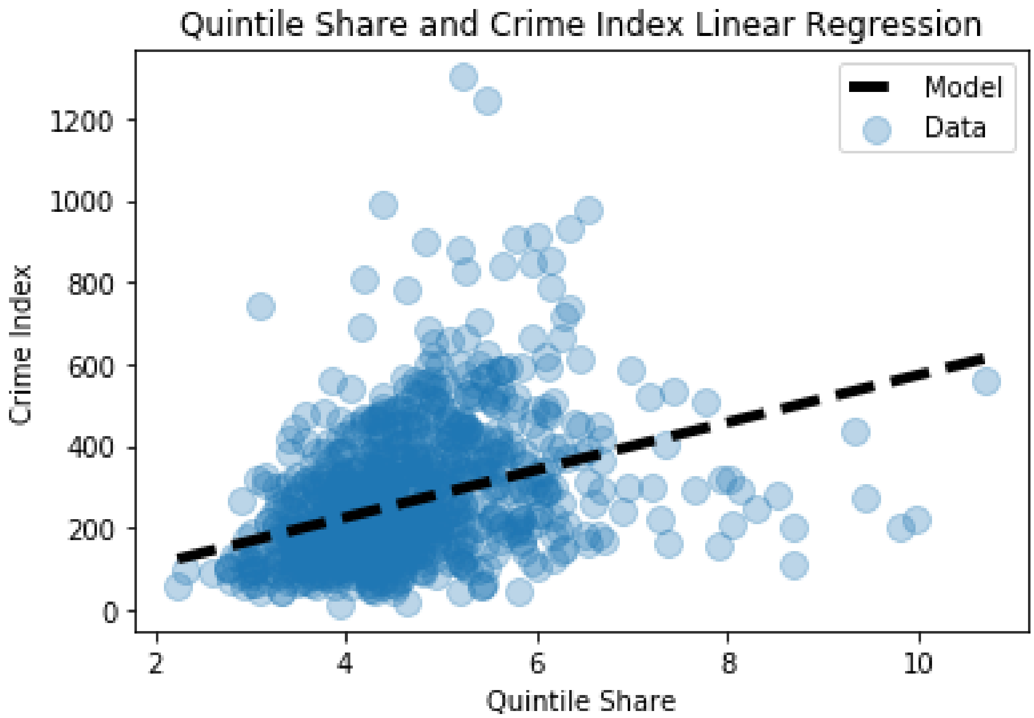
Now let's try a model that predicts the crime index values based off of the quintile share.

In [30]:
```
# Linear regression using the continuous values for crime index and quintile share
outcome_3, predictors_3 = patsy.dmatrices('crimeindex ~ quintileshare',
                                          crime_income_df)
mod_3 = sm.OLS(outcome_3, predictors_3)
res_3 = mod_3.fit()
lm_3 = bool(res_3.pvalues[1] < 0.01)
if lm_3 == True:
    print("Quintile Share significantly predicts crime index.\n")
else:
    print("Quintile Share doesn't significantly predict crime index.\n")
```

```
print(res_3.summary())
```

```
Quintile Share significantly predicts crime index.

                            OLS Regression Results
==============================================================================
Dep. Variable:             crimeindex   R-squared:                       0.129
Model:                            OLS   Adj. R-squared:                  0.129
Method:                 Least Squares   F-statistic:                     137.1
Date:                Wed, 12 Jun 2019   Prob (F-statistic):           1.25e-29
Time:                        23:24:56   Log-Likelihood:                -5964.3
No. Observations:                 924   AIC:                         1.193e+04
Df Residuals:                     922   BIC:                         1.194e+04
Df Model:                           1
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept         7.3352     23.341      0.314      0.753     -38.472      53.142
quintileshare    57.9963      4.952     11.711      0.000      48.277      67.716
==============================================================================
Omnibus:                      288.899   Durbin-Watson:                   1.716
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1148.417
Skew:                           1.434   Prob(JB):                    4.21e-250
Kurtosis:                       7.647   Cond. No.                         22.6
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [31]:
```
# Plot the orginal data (as before)
plt.scatter(crime_income_df['quintileshare'], crime_income_df['crimeindex'],
            alpha=0.3, label='Data', s=100);

# Generate and plot the model fit line
xs = np.linspace(crime_income_df['quintileshare'].min(),
                 crime_income_df['quintileshare'].max())
ys = (57.9963 * xs) - 7.3352
plt.plot(xs, ys, '--k', linewidth=4, label='Model')

plt.title('Quintile Share and Crime Index Linear Regression')
plt.xlabel('Quintile Share')
plt.ylabel('Crime Index')
plt.legend();
plt.show()
```



In [32]:
```
# Look at the correlation between the high and low inequality groups
# and crime index
df_ineq_exists = pd.DataFrame(crime_income_df \
                              [crime_income_df['inequalityexists'] == 1])
df_no_ineq_exists = pd.DataFrame(crime_income_df \
                                 [crime_income_df['inequalityexists'] == 0])

df_ineq_ineqcrime = df_ineq_exists[['quintileshare', 'crimeindex']]
df_no_ineq_ineqcrime = df_no_ineq_exists[['quintileshare', 'crimeindex']]

corrs_ineq_ineqcrime = df_ineq_ineqcrime.corr()
corrs_no_ineq_ineqcrime = df_no_ineq_ineqcrime.corr()

corrs_ineq_ineqcrime
```

Out[32]:

	quintileshare	crimeindex
quintileshare	1.000000	0.123457
crimeindex	0.123457	1.000000

In [33]:
```
corrs_no_ineq_ineqcrime
```

Out[33]:

	quintileshare	crimeindex
quintileshare	1.000000	0.285439
crimeindex	0.285439	1.000000

There is a weak positive correlation between quintile share and crime index.

9.0.2 Summary of Quintile Share Analysis

Looking at both quintile share alone as well as quintile share and poverty together, we can see that both of these seem to be independent and significant influences on the level of crime. The second linear model (with the variable name mod_2) shows that there is a systematic difference with respect to crime levels between cities with income inequality and cities without income inequality. Model 3 (variable name mod_3) shows a predictive model based off of the quintile share. It gives us sense of the strength of this relationship. While it is certainly significant, the correlation is somewhat weak.

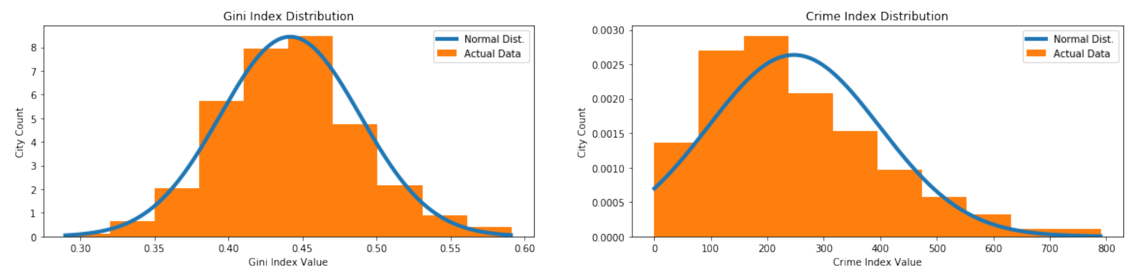
9.0.3 Gini Index Analysis

Now let's look at the Gini index data, another metric of determining income inequality which represents wealth distribution. First let's check if the Gini index and crime index data are normal to see if we can immediately run tests on it.

```
In [34]: # First, let us see if the Gini Index values are normal
         gini = crime_gini_df['Estimate; Gini Index']
         # Test to see if the gini index values are normal
         st_gini, p_gini = normaltest(gini)
         print(p_gini)
         if p_gini > 0.01:
             print('The Gini index distribution is approximately normal.')
         else:
             print('The Gini index distribution is not approximately normal.')

         # See if the crime index values are normal
         crimeindex = crime_gini_df['crime index']
         # Test to see if the crime index values are normal
         st_crime, p_crime = normaltest(crimeindex)
         print(p_crime)
         if p_crime > 0.01:
             print('The crime index distribution is approximately normal.')
         else:
             print('The crime index distribution is not approximately normal.')

         fig, axes = plt.subplots(nrows=1, ncols=2)
         ax0, ax1 = axes.flatten()

         xs0 = np.arange(min(gini), max(gini), 0.001)
         fit0 = stats.norm.pdf(xs0, np.mean(gini), np.std(gini))
         ax0.plot(xs0, fit0, label = 'Normal Dist.', lw = 4)
         ax0.hist(gini, density = True, label = 'Actual Data');
         ax0.set_title('Gini Index Distribution')
         ax0.set_xlabel('Gini Index Value')
         ax0.set_ylabel('City Count')
         ax0.legend();

         xs01 = np.arange(min(crimeindex), max(crimeindex), 0.001)
```

```
fit01 = stats.norm.pdf(xs01, np.mean(crimeindex), np.std(crimeindex))
ax1.plot(xs01, fit01, label = 'Normal Dist.', lw = 4)
ax1.hist(crimeindex, density = True, label = 'Actual Data');
ax1.set_title('Crime Index Distribution')
ax1.set_xlabel('Crime Index Value')
ax1.set_ylabel('City Count')
ax1.legend();

fig.set_size_inches(20, 4)
```

```
0.00013370632925130914
The Gini index distribution is not approximately normal.
8.454322024579447e-62
The crime index distribution is not approximately normal.
```

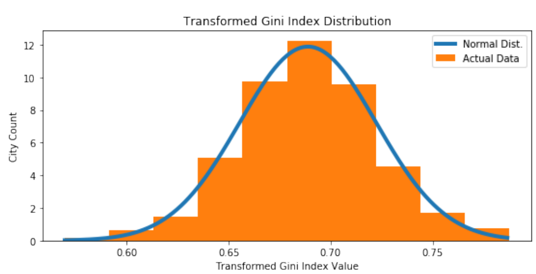


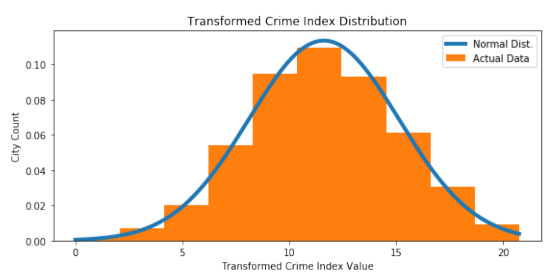
Since it is not normal, we are going to transform the data by taking a value to the power of 1/2.2 and test for normality again.

```
In [35]: # Transform the Gini index and crime index so they are normal
         transform_gini = []
         transform_crime = []
         for i in range(len(gini)):
             y = gini[i]**(1/2.2)
             k = crimeindex[i]**(1/2.2)
             transform_gini.append(y)
             transform_crime.append(k)

         # Test Gini index for normality again
         st_gini_transform, p_gini_transform = normaltest(transform_gini)
         print(p_gini_transform)
         if p_gini_transform > 0.01:
             print('The Gini index distribution is approximately normal.')
         else:
             print('The Gini index distribution is not approximately normal.')

         # Test crime index for normality again
         st_crime_transform, p_crime_transform = normaltest(transform_crime)
```

```python
print(p_crime_transform)
if p_crime_transform > 0.01:
    print('The crime index distribution is approximately normal.')
else:
    print('The crime index distribution is not approximately normal.')

fig1, axes1 = plt.subplots(nrows=1, ncols=2)
ax2, ax3 = axes1.flatten()

xs = np.arange(min(transform_gini), max(transform_gini), 0.001)
fit = stats.norm.pdf(xs, np.mean(transform_gini), np.std(transform_gini))
ax2.plot(xs, fit, label = 'Normal Dist.', lw = 4)
ax2.hist(transform_gini, density = True, label = 'Actual Data');
ax2.set_title('Transformed Gini Index Distribution')
ax2.set_xlabel('Transformed Gini Index Value')
ax2.set_ylabel('City Count')
ax2.legend();

xs1 = np.arange(min(transform_crime), max(transform_crime), 0.001)
fit1 = stats.norm.pdf(xs1, np.mean(transform_crime), np.std(transform_crime))
ax3.plot(xs1, fit1, label = 'Normal Dist.', lw = 4)
ax3.hist(transform_crime, density = True, label = 'Actual Data');
ax3.set_title('Transformed Crime Index Distribution')
ax3.set_xlabel('Transformed Crime Index Value')
ax3.set_ylabel('City Count')
ax3.legend();

fig1.set_size_inches(20, 4)

# Create a new column for the transformed Gini Index
# and rewrite crime index column
crime_gini_df['TransformedGini'] = transform_gini
crime_gini_df['crime index'] = transform_crime
```

```
0.023377379473207744
The Gini index distribution is approximately normal.
0.1170495969245683
The crime index distribution is approximately normal.
```





Now that the Gini index and crime index are normalized, lets look at how they are related and run some tests. First we create a table of correlation between crime index and Gini index. As we can see, there is a correlation of 0.33 and it is slightly less than the correlation we saw between quintile share and crime index but it is still a weak positive correlation.

```
In [36]: # Correlation between crime index and Gini index
         corrleation = crime_gini_df[['crime index', 'TransformedGini']].corr()
         corrleation
```

```
Out[36]:                  crime index  TransformedGini
         crime index         1.000000         0.329588
         TransformedGini     0.329588         1.000000
```

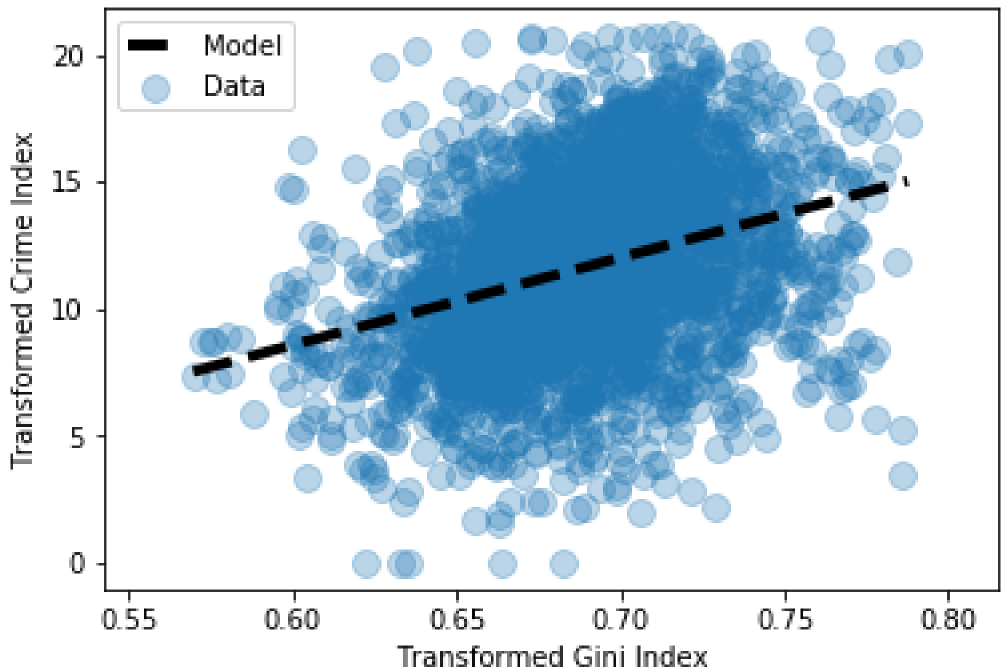
Similar to how we looked at quintile share and crime index, we want to look at a linear model to see if Gini index significantly can determind crime index. We will use Ordinary Least Squares (OLS) again for our modeling using patsy and statsmodels.

```
In [37]: # Rename crime index column to check
         crime_gini_df.rename(columns = {'crime index': 'crimeindex'},
                              inplace = True)
         outcome, predictors = patsy.dmatrices('crimeindex ~ TransformedGini',
                                               crime_gini_df)
         mod = sm.OLS(outcome, predictors)
         # fit the model
         res = mod.fit()

         lm = bool(res.pvalues[1] < 0.01)
         if lm == True:
             print("Gini Index significantly predicts crime index.\n")
         else:
             print("Gini Index doesn't significantly predict crime index.\n")

         ## look at the results
         print(res.summary())
```

```
Gini Index significantly predicts crime index.

                            OLS Regression Results
==============================================================================
Dep. Variable:             crimeindex   R-squared:                       0.109
Model:                            OLS   Adj. R-squared:                  0.108
Method:                 Least Squares   F-statistic:                     337.1
Date:                Wed, 12 Jun 2019   Prob (F-statistic):           3.92e-71
Time:                        23:25:00   Log-Likelihood:                -7246.6
No. Observations:                2768   AIC:                         1.450e+04
Df Residuals:                    2766   BIC:                         1.451e+04
Df Model:                           1
```

```
Covariance Type:            nonrobust
==================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept      -12.1309      1.295     -9.366      0.000     -14.671      -9.591
TransformedGini  34.4819      1.878     18.360      0.000      30.799      38.165
==============================================================================
Omnibus:                        8.272   Durbin-Watson:                   2.081
Prob(Omnibus):                  0.016   Jarque-Bera (JB):                8.236
Skew:                          -0.132   Prob(JB):                       0.0163
Kurtosis:                       3.044   Cond. No.                         43.9
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
In [38]: # Plot the orginal data (as before)
         plt.scatter(crime_gini_df['TransformedGini'], crime_gini_df['crimeindex'],
                     alpha=0.3, label='Data', s=100);

         # Generate and plot the model fit line
         xs2 = np.linspace(crime_gini_df['TransformedGini'].min(),
                           crime_gini_df['TransformedGini'].max())
         ys2 = (34.4819 * xs2) - 12.1309
         plt.plot(xs2, ys2, '--k', linewidth=4, label='Model')

         plt.xlabel('Transformed Gini Index')
         plt.ylabel('Transformed Crime Index')
         plt.legend();
         plt.show()
```



Let's quickly look at how the Gini index is also related to specific types of crimes. As we can see in the correlation table below, there the highest positive correlations besides crime index are with thefts, robberies, and burglaries per 100,000 population. This would make sense in areas with high income inequality that property crimes are also high.

In [39]:
```
# Find the correlation and section out the transformed gini index value
corr = crime_gini_df.corr()
ginicorr = corr['TransformedGini']
# Sort correlation from highest to lowest and look at the top six values
sortedcorr = ginicorr.sort_values(ascending = False)
sortedcorr.head(6)
```

Out[39]:
```
TransformedGini          1.000000
Estimate; Gini Index     0.999032
crimeindex               0.329588
theftsper100k            0.288551
robberiesper100k         0.286284
burglariesper100k        0.270550
Name: TransformedGini, dtype: float64
```

9.0.4 Summary of Gini Index Analysis

The Gini Index tells a fairly similar story as the quintile share does. Although it does so weakly, Income inequality significantly correlates with crime levels. Our analysis of the gini index data adds strength to our quintile share analysis, because it ensures us that our results were not a mere artifact of our particular way of quantifying income inequality.

10 Ethics & Privacy

For common problems among ethics and privacy when collecting data, many did not apply to our study, such as informed consent and collection bias, due to fact that we did not use human subjects for our projects and are using public & government datasets. However, ethical issues we may need to consider would include the disclosure of data of minors, for example the perpetrator of a juvenile crime. Perhaps we can use data where crimes of minors are included as long as identities are anonymous or unknown. At first, we considered focusing our project solely on the crimes performed by persons of legal age, thus removing information about minors from our datasets. All of the data sets we have looked at right now are public datasets, so we should be fine as far as permissions are concerned. Any identifying information have already been redacted to maintain confidentiality. If we encounter any data that seems to be a breach of confidentiality, we will follow the Safe Harbour method to remove any personally identifiable information. Using a default ethics checklist to cross-reference possible issues helped us think more abbout who will be affected by our research and what ways we can use to ensure prevention in harming others.

In terms of bias, there could be bias in the crime reporting and data that we are looking at since it is collected by humans. We also have to be aware of the bias and cultural issues around reporting certain crimes such as rape or hate crimes. For other ethical issues to consider is honest representation of the data and consider if the data we've grabbed from public sources and the government are always reliable. For crime, data is collected from public records and the other source is the US Census Bureau, a public government source.

In terms of whether our research can indirectly harm others and serve as a source for others to profit off of, it's possible that there's always a chance to represent a source incorrectly. Our analysis results could also be used for laws and policies that negatively affect people. However, what we'll do to at least control some of this possibility is to not make outlandish claims from our data and stick with a factual conclusion truly based on what the data is showing.

References: - 1) Data Science Ethics Checklist: http://deon.drivendata.org/#default-checklist - 2) Institute for Social Research: https://www.icpsr.umich.edu/icpsrweb/ - 3) U.S. Census Bureau: https://census.gov/

11 Conclusion & Discussion

What we had wanted to answer was whether or not income inequality played a role in crime levels in United States cities. To answer this question, we first gathered data from three sources, which you can read more about in the Datasets section. One dataset observed the number of crimes committed as well as the number of crimes committed per 100,000 persons in the population for each city. Crimes taken into account include murder, rape, robbery, assault, burglary, theft, auto theft, and arson; the dataset included a crime index value for each city reflecting the crimes committed. Another dataset measured each city's Gini index, which is a statistical measure used to gauge economic inequality, measuring income distribution among a population. The remaining dataset read incomes at different percentiles for each city.

For our analysis, we first checked for correlation visually and numerically. To get a better look of the comparison between cities with and without income inequality, we split our data accordingly and first checked if our data was normally distributed. It wasn't, so we transformed our data so that we could apply parametric tests. From there we saw a significant difference in crime index where there was and wasn't income inequality. We then went on to check if poverty had any influence. While the ratio of poverty existing was significantly different between the two, it appears that it does not alter the fact that income inequality has an affect on crime index. Although we found a positive relationship for crime index on income inequality, it's but a weak one, so income inequality should not be a reliable predictor of criminal activity. We ran similar tests against the Gini index to further support our findings.

Our project could be biased and inaccurate if our data is affected by biased reporting of criminal activity, government withholding of information, falsified income reportings, and the list goes on. Although we face limitations on what information we could get ahold of and on how accurate the information is, based on what we gathered, we have concluded that there is indeed a positive relationship between the two-- that crime index does in fact seem to increase with income inequality. Can we say that income inequality directly causes crime though? Probably not, as there could be many environmental or political factors to consider. From our analysis, we actually saw that more cities in areas without income inequality experience poverty, yet this did not affect crime being significantly affected by income inequality. Our findings could possibly encourage the public to understand other possible economic influences on crime levels aside from poverty. A less wealthy neighborhood doesn't necessarily mean more crimes are bound to occur. Rather, society might see that crimes occur more often in areas where the rich are much richer than the poor are poor, or in other words, areas where income inequality is undeniably evident.