Ratgression

May 12, 2025

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# 2 Data Collection

## 2.1 Data: 311

[45]:
```
import pandas as pd
import numpy as np
from dotenv import load_dotenv
import os
```

[46]:
```
# API Setup
load_dotenv()
NYC_OPENDATA_TOKEN = os.getenv('NYC_OPENDATA_TOKEN')

# Check that they were successfully accessed

if NYC_OPENDATA_TOKEN:
  print('NYC_OPENDATA tocken retrieved successfully.')
else:
  print('Could not find NYC_OPENDATA :(')
```

```
NYC_OPENDATA tocken retrieved successfully.
```

[47]:
```python
import requests
import time
from tqdm import tqdm
```

[48]:
```python
start_year = 2010
end_year = 2023
# The data is available from 2010 to 2022. This is because our Census data is␣
↪up to 2022.
```

[49]:
```python
# Setup

# NYC Open Data 311 API setup
APP_TOKEN = NYC_OPENDATA_TOKEN
BASE_URL = "https://data.cityofnewyork.us/resource/erm2-nwe9.json"
headers = {"X-App-Token": APP_TOKEN}

# Years and complaint types to query
years = list(range(start_year, end_year))

target_complaints = [
    "Dirty Condition", "Missed Collection", "Rodent", "Illegal Dumping",
    "Dead Animal", "Noise - Residential", "Noise - Vehicle", "Noise -␣
↪Helicopter",
    "Street Condition", "Sidewalk Condition", "Street Sign - Missing",
    "Broken Parking Meter", "Curb Condition", "Snow or Ice", "Mold",
    "Air Quality", "Water Maintenance", "Sewer Maintenance", "Trapping Pigeon",
    "Unleashed Dog", "Overgrown Tree/Branches", "Dead/Dying Tree"
]

# Map borough names to standard 2-letter codes
borough_codes = {
    "MANHATTAN": "MN",
    "BRONX": "BX",
    "BROOKLYN": "BK",
    "QUEENS": "QN",
    "STATEN ISLAND": "SI"
}
```

[50]:
```python
all_counts = []

for year in years:
    print(f"\nGetting 311 complaint counts for {year}...")

    # Build WHERE clause
    date_filter = (
        f"created_date >= '{year}-01-01T00:00:00' AND "
        f"created_date < '{year + 1}-01-01T00:00:00'"
```

```
    )
    complaint_filter = " OR ".join([
        f"upper(complaint_type) LIKE '%{c.upper()}%'" for c in target_complaints
    ])
    where_clause = f"{date_filter} AND ({complaint_filter}) AND community_board␣
↪IS NOT NULL"

    # Request from API
    params = {
        "$select": "community_board, count(*) as count",
        "$where": where_clause,
        "$group": "community_board"
    }

    response = requests.get(BASE_URL, headers=headers, params=params)
    data = pd.DataFrame(response.json())

    if data.empty:
        print(f"No data returned for {year}")
        continue

    # Convert and extract geo_id
    data["count"] = data["count"].astype(int)
    parts = data["community_board"].str.upper().str.extract(r"^(\d{2})\s+([A-Z␣
↪]+)$")
    data["geo_id"] = parts[1].str.strip().map(borough_codes) + parts[0]

    # Preview rows with bad geo_id
    bad_geo_rows = data[data["geo_id"].isna()]
    n_bad = len(bad_geo_rows)

    # Drop invalid rows
    data = data.dropna(subset=["geo_id"])

    # Group to ensure no duplicates and rename column
    data = (
        data.groupby("geo_id", as_index=True)["count"]
        .sum()
        .rename(year) # .rename(f"311_{year}")
        .to_frame()
    )

    all_counts.append(data)

    print(f"Year {year}... {len(data)} districts ({n_bad} bad rows dropped)")
```

```
Getting 311 complaint counts for 2010…
Year 2010… 70 districts (6 bad rows dropped)

Getting 311 complaint counts for 2011…
Year 2011… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2012…
Year 2012… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2013…
Year 2013… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2014…
Year 2014… 70 districts (6 bad rows dropped)

Getting 311 complaint counts for 2015…
Year 2015… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2016…
Year 2016… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2017…
Year 2017… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2018…
Year 2018… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2019…
Year 2019… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2020…
Year 2020… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2021…
Year 2021… 71 districts (6 bad rows dropped)

Getting 311 complaint counts for 2022…
Year 2022… 71 districts (6 bad rows dropped)
```

[51]:

```
# Combine into one DataFrame
combined_311_df = (
    pd.concat(all_counts, axis=1)
    .fillna(0)
    .astype(int)
    .reset_index()  #  brings geo_id back as a regular column
)
```

[52]:
```
combined_311_df
```

[52]:
```
    geo_id  2010  2011  2012  2013   2014   2015   2016   2017   2018   2019  \
0     BK01  6587  6751  6939  7673  12670  12941  13277  13229  14684  17081
1     BK02  4827  5278  4485  5119   7089   8021  12252   8866   9524  10479
2     BK03  6828  7078  7692  8389  10845  13086  13009  13107  14109  15360
3     BK04  4261  4476  5023  5876   8074   9238   9703  10589  10005  13702
4     BK05  6867  6804  6710  6889   8994  11313  10154  11105  11130  11732
..     ...   ...   ...   ...   ...    ...    ...    ...    ...    ...    ...
66    SI01  8153  8345  8299  8546  11800  15410  13828  13939  16607  16985
67    SI02  5363  5806  5245  5708   7646  10275   9439   9693  10185  10735
68    SI03  6160  6376  6252  7148   8595  13161  10711  12072  12340  14360
69    SI95    10     7     5    13     19     10     12     14     37     48
70    QN84     0     6     3     9     15     27     13     14     19     38

     2020   2021   2022
0   19009  19103  19943
1   10331  11676  13127
2   16882  18882  18236
3   14519  14272  13239
4   15474  17874  15597
..    ...    ...    ...
66  16991  19124  15521
67   9461  12978  12492
68  13820  18234  16322
69     28     18    108
70     46     40     20

[71 rows x 14 columns]
```

### 2.2 Data: Shootings

[53]:
```
# Constants
APP_TOKEN = NYC_OPENDATA_TOKEN
BASE_URL = "https://data.cityofnewyork.us/resource/833y-fsy8.json"
LIMIT = 1000
TOTAL_ROWS = 29744

# Set headers
headers = {
    "X-App-Token": APP_TOKEN
}

# Initialize
raw_crime_data = []

# Calculate number of batches
```

```python
num_batches = (TOTAL_ROWS // LIMIT) + 1

# Loop with progress bar
for offset in tqdm(range(0, TOTAL_ROWS, LIMIT), desc="Downloading NYPD Data"):
    params = {
        "$limit": LIMIT,
        "$offset": offset
    }
    response = requests.get(BASE_URL, params=params, headers=headers)
    crime_data = response.json()

    if not crime_data:
        break

    raw_crime_data.extend(crime_data)
    time.sleep(0.1)  # Be polite to the API
```

```
Downloading NYPD Data: 100%|      | 30/30 [00:14<00:00,  2.07it/s]
```

[54]:

```python
all_crime_data = pd.DataFrame(raw_crime_data)
```

NYPD data is by precinct, but we want to work with community districts. Unfortunately, some precincts do not neatly overlap with community districts. So we're instead going to use the latitude and longitude of the complaints, and map those to the community districts.

[55]:

```python
# Drop any rows that have zero or NaN values in 'latitude' and 'longitude'
all_crime_data.loc[:, "latitude"] = pd.to_numeric(all_crime_data["latitude"])
all_crime_data.loc[:, "longitude"] = pd.to_numeric(all_crime_data["longitude"])

all_crime_data = all_crime_data[
    all_crime_data["latitude"].notna() &
    all_crime_data["longitude"].notna() &
    (all_crime_data["latitude"] != 0.0) &
    (all_crime_data["longitude"] != 0.0)
]
all_crime_data
```

[55]:

```
       incident_key               occur_date occur_time       boro  \
0         298699604  2024-12-31T00:00:00.000   19:16:00   BROOKLYN
1         298699604  2024-12-31T00:00:00.000   19:16:00   BROOKLYN
2         298672096  2024-12-30T00:00:00.000   16:45:00      BRONX
3         298672096  2024-12-30T00:00:00.000   16:45:00      BRONX
4         298672095  2024-12-30T00:00:00.000   20:32:00      BRONX
…               …                       …          …          …
29739       9953250  2006-01-01T00:00:00.000   02:34:00     QUEENS
29740       9953245  2006-01-01T00:00:00.000   02:00:00      BRONX
29741     139716503  2006-01-01T00:00:00.000   12:30:00   BROOKLYN
29742       9953246  2006-01-01T00:00:00.000   05:51:00      BRONX
```

```
29743      9953252  2006-01-01T00:00:00.000   02:22:00  MANHATTAN

      loc_of_occur_desc precinct jurisdiction_code loc_classfctn_desc  \
0               OUTSIDE       69                 0             STREET
1               OUTSIDE       69                 0             STREET
2               OUTSIDE       47                 0             STREET
3               OUTSIDE       47                 0             STREET
4                INSIDE       41                 0           DWELLING
…                     …        …                 …                  …
29739               NaN      114                 0                NaN
29740               NaN       48                 0                NaN
29741               NaN       77                 0                NaN
29742               NaN       44                 0                NaN
29743               NaN       28                 0                NaN

                 location_desc  statistical_murder_flag  …  \
0                       (null)                    False  …
1                       (null)                    False  …
2                       (null)                    False  …
3                       (null)                    False  …
4      MULTI DWELL - APT BUILD                     True  …
…                            …                        …  …
29739            BAR/NIGHT CLUB                    True  …
29740                      NONE                   False  …
29741                 PVT HOUSE                    True  …
29742                      NONE                   False  …
29743                      NONE                    True  …

                    x_coord_cd              y_coord_cd   latitude  longitude  \
0                    1,015,120                 173,870  40.643866 -73.888761
1                    1,015,120                 173,870  40.643866 -73.888761
2                    1,021,316                 259,277  40.878261 -73.865964
3                    1,021,316                 259,277  40.878261 -73.865964
4                    1,012,201                 240,878  40.827795 -73.899003
…                            …                       …          …          …
29739  1002576.750000000000000  221583.453125000000000  40.774861 -73.933833
29740  1013404.562500000000000  251800.750000000000000   40.85777 -73.894607
29741   996441.562500000000000  184160.359375000000000  40.672154 -73.956052
29742  1007418.000000000000000  243859.218750000000000   40.83599 -73.916276
29743   998815.750000000000000  233545.437500000000000    40.8077 -73.947386

                                         geocoded_column  \
0      {'type': 'Point', 'coordinates': [-73.888761, …
1      {'type': 'Point', 'coordinates': [-73.888761, …
2      {'type': 'Point', 'coordinates': [-73.865964, …
3      {'type': 'Point', 'coordinates': [-73.865964, …
4      {'type': 'Point', 'coordinates': [-73.899003, …
```

```
…                                                    …
29739  {'type': 'Point', 'coordinates': [-73.93383258…
29740  {'type': 'Point', 'coordinates': [-73.89460745…
29741  {'type': 'Point', 'coordinates': [-73.95605150…
29742  {'type': 'Point', 'coordinates': [-73.91627635…
29743  {'type': 'Point', 'coordinates': [-73.94738575…

      :@computed_region_yeji_bk3q :@computed_region_92fq_4b7q  \
0                               2                           8
1                               2                           8
2                               5                           2
3                               5                           2
4                               5                          43
…                             …                           …
29739                           3                           4
29740                           5                          22
29741                           2                          48
29742                           5                          42
29743                           4                          36

      :@computed_region_sbqj_enih :@computed_region_efsh_h5xi  \
0                              42                       13827
1                              42                       13827
2                              30                       11605
3                              30                       11605
4                              25                       10937
…                             …                           …
29739                          72                       16859
29740                          29                       10936
29741                          49                       17618
29742                          27                       10934
29743                          18                       12424

      :@computed_region_f5dn_yrer
0                               5
1                               5
2                              29
3                              29
4                              34
…                             …
29739                          39
29740                           6
29741                          16
29742                          50
29743                          18

[29647 rows x 26 columns]
```

---

[56]:
```python
from shapely.geometry import Point
import geopandas as gpd
```

[57]:
```python
# 1. Load the community districts GeoJSON
cd_gdf = gpd.read_file("CD.geo.json")

# 2. Extract geo_id from GEONAME and format (e.g., CD01, CD13)
cd_gdf["geo_id"] = (
    cd_gdf["BOROUGH"].str.upper().map(borough_codes) +
    cd_gdf["GEONAME"].str.extract(r"\(CD(\d{1,2})\)")[0].str.zfill(2)
)

# 3. Create geometry column for crime data
geometry = [Point(xy) for xy in zip(all_crime_data["longitude"],␣
 ↪all_crime_data["latitude"])]
crime_gdf = gpd.GeoDataFrame(all_crime_data, geometry=geometry, crs="EPSG:4326")

# 4. Ensure same CRS
cd_gdf = cd_gdf.to_crs("EPSG:4326")

# 5. Spatial join
joined = gpd.sjoin(crime_gdf, cd_gdf[["geometry", "geo_id"]], how="left",␣
 ↪predicate="within")

# 6. Assign geo_id to original DataFrame
all_crime_data["geo_id"] = joined["geo_id"]
```

[58]:
```python
# Number of rows
len(all_crime_data)
```

[58]: 29647

[59]:
```python
# Some complaints (9) still have no geo_id. This is because they are on major␣
 ↪roads or bridges, not within a community district (I checked the dropped␣
 ↪rows separately).
# We are choosing to drop these rows, because they make up a very small␣
 ↪percentage of the data, and because they're not located within a community␣
 ↪district.
all_crime_data = all_crime_data.dropna(subset=["geo_id"])
```

[60]:
```python
# Number of rows
len(all_crime_data)
```

[60]: 29638

[61]:
```python
# Sum of shootings per community district in 2010

# 1. Convert dates
all_crime_data["occur_date"] = pd.to_datetime(all_crime_data["occur_date"],␣
↪errors="coerce")

# 2. Extract year
all_crime_data["year"] = all_crime_data["occur_date"].dt.year

# 3. Filter for after 2010 and before 2023
crime_filtered = all_crime_data[(all_crime_data["year"] >= start_year) &␣
↪(all_crime_data["year"] < end_year)]

# 4. Group and pivot
shooting_counts = (
    crime_filtered
    .groupby(["geo_id", "year"])
    .size()
    .unstack(fill_value=0)
    .rename_axis(None, axis=1)        # removes 'year' from top-left
    # .add_prefix("shootings_")         # adds prefix to column names
    .reset_index()                    # only resets geo_id
)
shooting_counts
```

```
C:\Users\Anant\AppData\Local\Temp\ipykernel_17388\326513934.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  all_crime_data["occur_date"] = pd.to_datetime(all_crime_data["occur_date"],
errors="coerce")
C:\Users\Anant\AppData\Local\Temp\ipykernel_17388\326513934.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  all_crime_data["year"] = all_crime_data["occur_date"].dt.year
```

[61]:

| | geo_id | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | \ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | BK01 | 27 | 27 | 20 | 17 | 23 | 35 | 22 | 21 | 22 | 8 | 30 | |
| 1 | BK02 | 27 | 21 | 24 | 14 | 21 | 34 | 15 | 16 | 15 | 16 | 29 | |
| 2 | BK03 | 137 | 134 | 116 | 93 | 102 | 74 | 91 | 58 | 68 | 62 | 125 | |

```
3    BK04    48    50    33    25    25    20    19    15    18    15    17
4    BK05   109   129    88    78    79    80    67    45    33    66   145
..    …    …    …    …    …    …    …    …    …    …    …    …
63   QN83     0     0     0     0     0     0     0     0     0     0     2
64   SI01    32    39    41    48    39    42    36    42    22    19    44
65   SI02     1     3     7     3     3     3     8     3     0     3     6
66   SI03     1     8     0     1     0     5     0     1     3     4     0
67   SI95     0     0     1     0     0     0     0     0     0     0     0

    2021  2022
0     22    21
1     22    20
2     92    65
3     49    26
4     95    88
..   …     …
63     0     0
64    34    36
65     4     1
66     2     3
67     0     0

[68 rows x 14 columns]
```

# 3 Data Analysis

## 3.1 Create Panel Data

[62]:
```python
panel_data = pd.DataFrame() # Initialize the empty DataFrame
```

[63]:
```python
shooting_long = shooting_counts.melt(id_vars="geo_id", var_name="year",␣
 ↪value_name="shootings")
complaints_long = combined_311_df.melt(id_vars="geo_id", var_name="year",␣
 ↪value_name="complaints")
panel_data = pd.merge(shooting_long, complaints_long, on=["geo_id", "year"],␣
 ↪how="outer")
```

Note: All community districts have a numerical code between 0 - 20. If it is 20 or greater, this means it is a Joint Interest Area, which includes parks and other zones that can be outliers for our data, and skew our regression. As a result, these Joint Interest Areas will be dropped.

[64]:
```python
panel_data["district_num"] = panel_data["geo_id"].str.extract(r"(\d{2})").
 ↪astype(int)
panel_data = panel_data[panel_data["district_num"] < 20].
 ↪drop(columns="district_num")
```

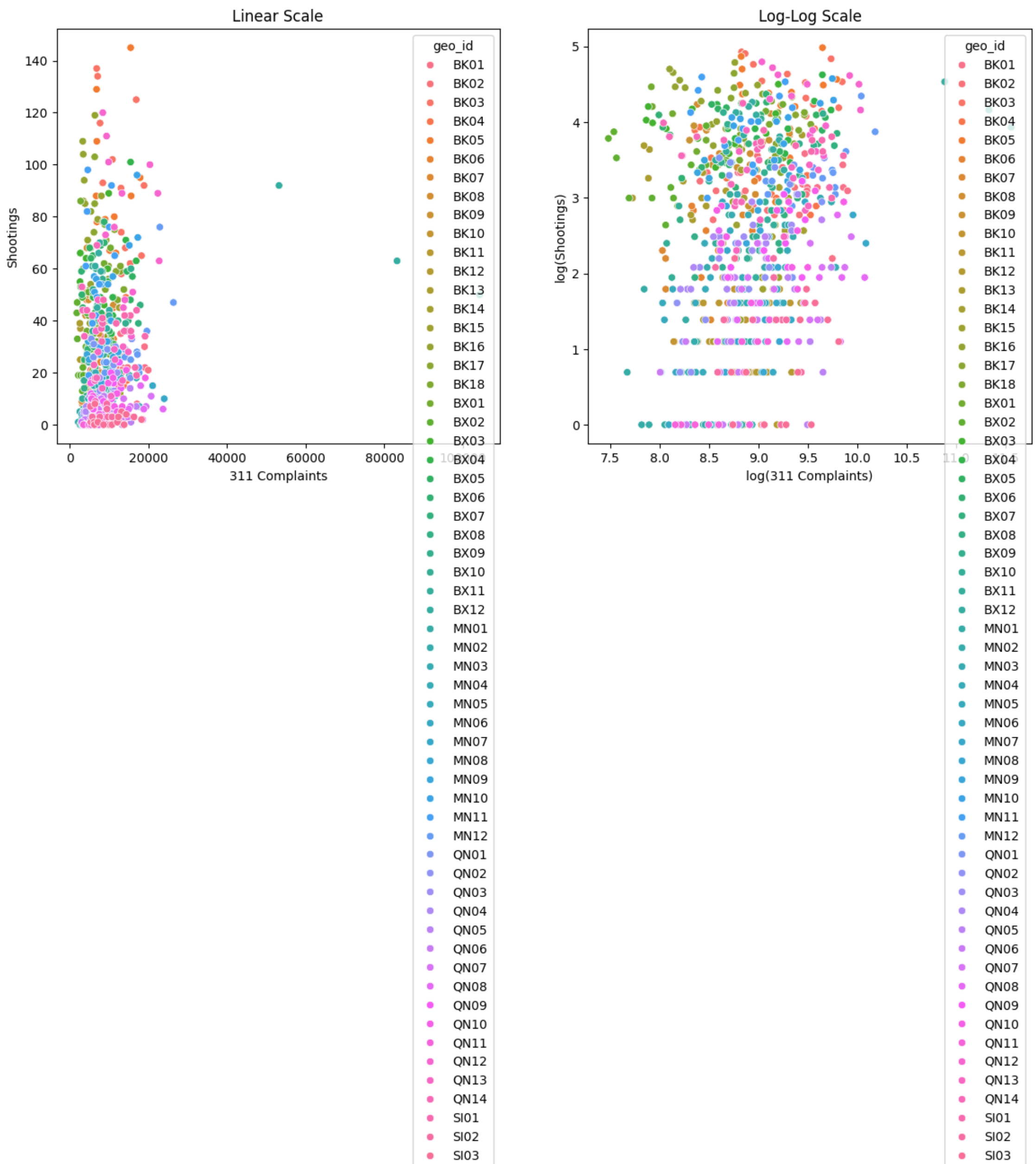
[65]:
```python
panel_data = panel_data.set_index(["geo_id", "year"]).sort_index()

# In case we need it, I'm also adding the logs of the complaints and shootings
panel_data["log_complaints"] = np.log(panel_data["complaints"] + 1)
panel_data["log_shootings"] = np.log(panel_data["shootings"] + 1)

# Preview data
panel_data.head()
```

[65]:

| | | shootings | complaints | log_complaints | log_shootings |
|---|---|---|---|---|---|
| geo_id | year | | | | |
| BK01 | 2010 | 27.0 | 6587 | 8.793005 | 3.332205 |
| | 2011 | 27.0 | 6751 | 8.817594 | 3.332205 |
| | 2012 | 20.0 | 6939 | 8.845057 | 3.044522 |
| | 2013 | 17.0 | 7673 | 8.945593 | 2.890372 |
| | 2014 | 23.0 | 12670 | 9.447071 | 3.178054 |

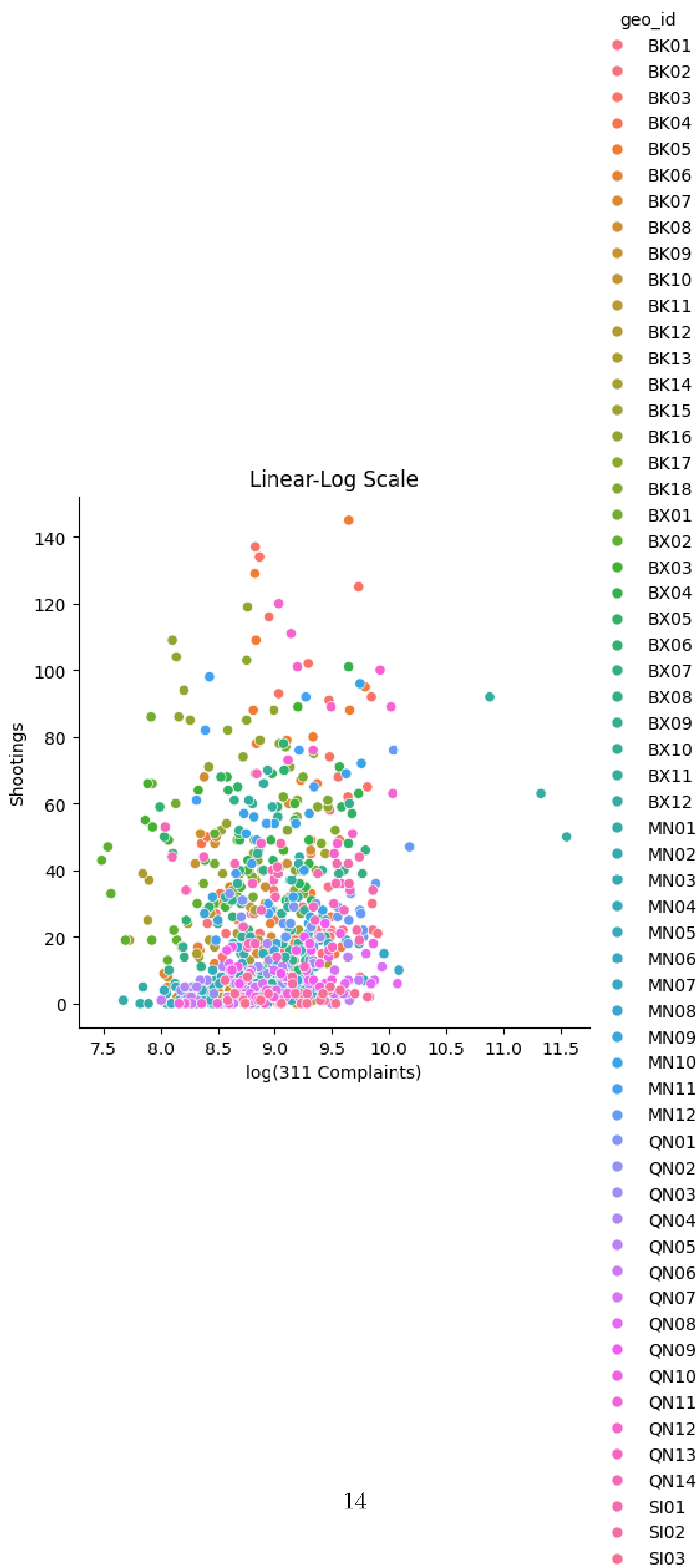
## 3.2 See the Pooled Data

[66]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

see_the_data = panel_data.reset_index()

# Create scatterplot
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Linear plot
sns.scatterplot(data=see_the_data, x="complaints", y="shootings", hue="geo_id",␣
    ↪ax=axes[0])
axes[0].set_title("Linear Scale")
axes[0].set_xlabel("311 Complaints")
axes[0].set_ylabel("Shootings")

# Log-log plot
sns.scatterplot(data=see_the_data, x="log_complaints", y="log_shootings",␣
    ↪hue="geo_id", ax=axes[1])
axes[1].set_title("Log-Log Scale")
axes[1].set_xlabel("log(311 Complaints)")
axes[1].set_ylabel("log(Shootings)")

plt.show()
```




[67]:
```python
# We ultimately used a linear-log plot, so let's see how that looks
sns.relplot(data=see_the_data, x="log_complaints", y="shootings",␣
 ↪kind="scatter", hue="geo_id")
plt.title("Linear-Log Scale")
plt.xlabel("log(311 Complaints)")
plt.ylabel("Shootings")
```

[67]:
```
Text(41.735163194444425, 0.5, 'Shootings')
```


Linear-Log Scale
Shootings
log(311 Complaints)
0
20
40
60
80
100
120
140
7.5
8.0
8.5
9.0
9.5
10.0
10.5
11.0
11.5
geo_id
BK01
BK02
BK03
BK04
BK05
BK06
BK07
BK08
BK09
BK10
BK11
BK12
BK13
BK14
BK15
BK16
BK17
BK18
BX01
BX02
BX03
BX04
BX05
BX06
BX07
BX08
BX09
BX10
BX11
BX12
MN01
MN02
MN03
MN04
MN05
MN06
MN07
MN08
MN09
MN10
MN11
MN12
QN01
QN02
QN03
QN04
QN05
QN06
QN07
QN08
QN09
QN10
QN11
QN12
QN13
QN14
SI01
SI02
SI03

### 3.3 Regression

[68]:
```
import linearmodels as lm
```

#### 3.3.1 Pooled Model

[69]:
```
pooled_model = lm.PooledOLS.from_formula('shootings ~ log_complaints + 1', data
 ↪= panel_data).fit(cov_type='clustered', cluster_entity=True)
# After playing around with various linear/log combinations, the lin-log model
 ↪seemed to have the clearest interpretation.


print(pooled_model.summary)
```

```
                          PooledOLS Estimation Summary
================================================================================
Dep. Variable:              shootings   R-squared:                        0.0208
Estimator:                  PooledOLS   R-squared (Between):              0.0419
No. Observations:                 767   R-squared (Within):              -0.0632
Date:                Mon, May 12 2025   R-squared (Overall):              0.0208
Time:                        19:23:49   Log-likelihood                   -3598.7
Cov. Estimator:             Clustered
                                        F-statistic:                      16.233
Entities:                          59   P-value                           0.0001
Avg Obs:                       13.000   Distribution:                   F(1,765)
Min Obs:                       13.000
Max Obs:                       13.000   F-statistic (robust):             3.1732
                                        P-value                           0.0753
Time periods:                      13   Distribution:                   F(1,765)
Avg Obs:                       59.000
Min Obs:                       59.000
Max Obs:                       59.000

                             Parameter Estimates
================================================================================
==
                Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper
CI
--------------------------------------------------------------------------------
--
Intercept         -43.948     38.752    -1.1341     0.2571     -120.02
32.125
log_complaints     7.7637     4.3583     1.7814     0.0753     -0.7920
16.319
================================================================================
```

==

### 3.3.2 Linear Panel

[70]:
```
panel = lm.PanelOLS.from_formula(
    "shootings ~ complaints + EntityEffects + TimeEffects", data = panel_data
    ).fit(cov_type='clustered',cluster_entity=True)

print(panel.summary)
```

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:              shootings   R-squared:                        0.0016
Estimator:                   PanelOLS   R-squared (Between):              0.0390
No. Observations:                 767   R-squared (Within):               0.0026
Date:                Mon, May 12 2025   R-squared (Overall):              0.0352
Time:                        19:23:49   Log-likelihood                   -2858.9
Cov. Estimator:             Clustered
                                        F-statistic:                      1.1241
Entities:                          59   P-value                           0.2894
Avg Obs:                       13.000   Distribution:                   F(1,695)
Min Obs:                       13.000
Max Obs:                       13.000   F-statistic (robust):             4.2670
                                        P-value                           0.0392
Time periods:                      13   Distribution:                   F(1,695)
Avg Obs:                       59.000
Min Obs:                       59.000
Max Obs:                       59.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
complaints  9.848e-05  4.767e-05     2.0657     0.0392   4.876e-06      0.0002
==============================================================================

F-test for Poolability: 58.035
P-value: 0.0000
Distribution: F(70,695)

Included effects: Entity, Time
```

### 3.3.3 Log Panel

[71]:
```
panel = lm.PanelOLS.from_formula(
    "shootings ~ log_complaints + EntityEffects + TimeEffects", data =␣
 ↪panel_data
    ).fit(cov_type='clustered',cluster_entity=True)
```

```python
print(panel.summary)
```

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:              shootings   R-squared:                        0.0051
Estimator:                   PanelOLS   R-squared (Between):              0.2135
No. Observations:                 767   R-squared (Within):              -0.0295
Date:                Mon, May 12 2025   R-squared (Overall):              0.1879
Time:                        19:23:49   Log-likelihood                   -2857.5
Cov. Estimator:             Clustered
                                        F-statistic:                      3.5609
Entities:                          59   P-value                           0.0596
Avg Obs:                       13.000   Distribution:                   F(1,695)
Min Obs:                       13.000
Max Obs:                       13.000   F-statistic (robust):             6.4073
                                        P-value                           0.0116
Time periods:                      13   Distribution:                   F(1,695)
Avg Obs:                       59.000
Min Obs:                       59.000
Max Obs:                       59.000

                              Parameter Estimates
================================================================================
==
                Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper
CI
--------------------------------------------------------------------------------
--
log_complaints     5.1011     2.0152     2.5313     0.0116      1.1444
9.0577
================================================================================
==

F-test for Poolability: 58.660
P-value: 0.0000
Distribution: F(70,695)

Included effects: Entity, Time
```

# 4 Conclusion

### Panel Model Equation

$$\text{shootings}_{it} = \beta_1 \cdot \log(\text{complaints}_{it} + 1) + \alpha_i + \delta_t + \varepsilon_{it}$$

- $i$ = community districts

- $t$ = years
- $\alpha_i$ are entity (community district) fixed effects
- $\delta_t$ are time (year) fixed effects
- The log is applied as $\log(x+1)$ to handle zero values

**Interpretation**

- At a 5% confidence level, we conclude that for every 1% increase in select 311 complaints, there is a 0.05 increase in shootings.
- This is taking into account effects that are:
  - Constant over time, but vary across Community Districts.
  - Constant over Community Districts, but vary across time.
- This would support the "broken windows" theory, that public order (clean streets, proper infrastructure) is correlated with public safety.

**Where the Data Came From**

- 311 data was pulled from the NYC OpenData API, and is available at this link.
- Similarly, NYPD Shooting Incident data was pulled from the NYC OpenData API, and is available at this link.
- This NYPD data had to be modified to specify in which Community District each shooting occurred. The geo.json file used to make this modification was retrieved from this Github project.
- Data on Community Districts is, as of now, unused. This data came from the American Community Survey, and was organized by the NYC Department of Planning. It is available at this link.

# 5 Extra Extra: Experimenting with Census Data

*We ultimately chose against including data from the American Community Survey, as we lacked data for 2011-2017, and the data we did have were 5-year averages, which might have led to unnatural jumps without interpolation.*

*In the following code, we experimented with using the ACS data. We focused on the median income, the percentage of people working from home, and the percentage of people under 50% of the poverty line.*

*We used the 2006-2010 averages as the values for 2010, used the 2018-2022 averages as the values for 2020, and used regular linear interpolation for the data in-between. This is problematic because the data is almost certainly not linear: the pandemic should result in wonky data around 2020.*

*Ultimately, including these variables did not significantly impact the coefficient of* $log(complaints_{it})$*. They did raise the* $R^2$ *to 0.0186, from 0.0051.*

*But because the coefficient of* $log(complaints_{it})$ *did not significantly change, and because none of these variables were themselves significant, we felt comfortable using the original panel model.*

### 5.1 Census Data (American Community Survey)

[72]:
```
import openpyxl
```

[73]:
```
econ_0610 = pd.read_excel("2010_ACS.xlsx", sheet_name="EconData") # Data from
↪the 2006-2010 ACS 5-Year Estimates
econ_1822 = pd.read_excel("2022_ACS.xlsx", sheet_name="EconData") # Data from
↪the 2018-2022 ACS 5-Year Estimates
```

[74]:
```
# Step 1: Add 'year' column
econ_0610["year"] = 2010
econ_1822["year"] = 2020

# Step 2: Select relevant variables
selected_cols = ["GeoID", "MnHHIncM", "CW_WrkdHmP", "PvU50E", "year"]
# We're getting the median income, the percentage of people working from home,
↪and the percentage of people under 50% of the poverty line.

econ_0610 = econ_0610[selected_cols]
econ_1822 = econ_1822[selected_cols]

# Step 3: Standardize column names and rename for clarity
rename_map = {
    "GeoID": "geo_id",
    "MnHHIncM": "median_income",
    "CW_WrkdHmP": "pct_work_from_home",
    "PvU50E": "pct_under_poverty_50"
}

for df in [econ_0610, econ_1822]:
    df.rename(columns=rename_map, inplace=True)
```

[75]:
```
# Step 4: Combine into a single DataFrame
econ_data = pd.concat([econ_0610, econ_1822], ignore_index=True)
econ_data = econ_data.sort_values(["geo_id", "year"]).reset_index(drop=True)
```

[76]:
```
# 1. Create full index of geo_id × years
full_index = pd.MultiIndex.from_product(
    [econ_data["geo_id"].unique(), range(2010, 2023)],
    names=["geo_id", "year"]
)

# 2. Reindex to fill missing years
econ_data = econ_data.set_index(["geo_id", "year"]).reindex(full_index).
↪sort_index()

# 3. Interpolate values for missing years
```

```
econ_data = econ_data.groupby(level=0, group_keys=False).apply(lambda g: g.
 ↪interpolate()).reset_index()
```

[77]:
```
econ_data
```

[77]:
```
    geo_id  year  median_income  pct_work_from_home  pct_under_poverty_50
0     BK01  2010         1998.0                6.60               23412.0
1     BK01  2011         2322.2                8.02               23026.5
2     BK01  2012         2646.4                9.44               22641.0
3     BK01  2013         2970.6               10.86               22255.5
4     BK01  2014         3294.8               12.28               21870.0
..     …     …             …                  …                    …
918   SI95  2018        38763.2                1.40                   0.0
919   SI95  2019        41804.1                1.40                   0.0
920   SI95  2020        44845.0                1.40                   0.0
921   SI95  2021        44845.0                1.40                   0.0
922   SI95  2022        44845.0                1.40                   0.0

[923 rows x 5 columns]
```

### 5.2 Panel model with Census data

[78]:
```
# Get rid of community districts above 20
econ_data["district_num"] = econ_data["geo_id"].str.extract(r"(\d{2})").
 ↪astype(int)
econ_data = econ_data[econ_data["district_num"] < 20].
 ↪drop(columns="district_num")
```

[79]:
```
# 1. Ensure econ_data has matching index format
econ_data = econ_data.set_index(["geo_id", "year"]).sort_index()

# 2. Join to panel_data (preserves existing index)
panel_data = panel_data.join(econ_data, how="left")

# 3. Put median income in log scale
panel_data["log_median_income"] = np.log(panel_data["median_income"] + 1)
```

[80]:
```
ACS_model = lm.PanelOLS.from_formula(
    "shootings ~ log_complaints + log_median_income + pct_under_poverty_50 +␣
 ↪pct_work_from_home + EntityEffects + TimeEffects",
    data=panel_data
).fit(cov_type="clustered", cluster_entity=True)

print(ACS_model.summary)
```

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:              shootings   R-squared:                        0.0186
```

```
Estimator:                   PanelOLS   R-squared (Between):           -16.169
No. Observations:                 767   R-squared (Within):            -0.4569
Date:                Mon, May 12 2025   R-squared (Overall):           -14.518
Time:                        19:23:51   Log-likelihood                 -2852.3
Cov. Estimator:             Clustered
                                        F-statistic:                    3.2707
Entities:                          59   P-value                         0.0114
Avg Obs:                       13.000   Distribution:                 F(4,692)
Min Obs:                       13.000
Max Obs:                       13.000   F-statistic (robust):           3.3575
                                        P-value                         0.0098
Time periods:                      13   Distribution:                 F(4,692)
Avg Obs:                       59.000
Min Obs:                       59.000
Max Obs:                       59.000

                                  Parameter Estimates
================================================================================
========
                      Parameter  Std. Err.     T-stat    P-value    Lower CI
Upper CI
--------------------------------------------------------------------------------
--------
log_complaints           5.0641     2.2422     2.2585     0.0242      0.6617
9.4665
log_median_income        13.138     8.0616     1.6297     0.1036     -2.6899
28.966
pct_under_poverty_50     0.0008     0.0006     1.4454     0.1488     -0.0003
0.0019
pct_work_from_home       0.3484     0.2602     1.3391     0.1810     -0.1625
0.8593
================================================================================
========

F-test for Poolability: 29.779
P-value: 0.0000
Distribution: F(70,692)

Included effects: Entity, Time
```

[81]:

```
from linearmodels.panel import compare

compare_models = compare(
    {"Restricted": panel, "Full": ACS_model},
    precision='std_errors'
)
```

[82]:
```python
print(compare_models)
```

```
                  Model Comparison
====================================================
                            Restricted          Full
----------------------------------------------------
Dep. Variable                shootings     shootings
Estimator                     PanelOLS      PanelOLS
No. Observations                   767           767
Cov. Est.                    Clustered     Clustered
R-squared                       0.0051        0.0186
R-Squared (Within)             -0.0295       -0.4569
R-Squared (Between)             0.2135       -16.169
R-Squared (Overall)             0.1879       -14.518
F-statistic                     3.5609        3.2707
P-value (F-stat)                0.0596        0.0114
======================     ===========   ===========
log_complaints                  5.1011        5.0641
                              (2.0152)      (2.2422)
log_median_income                             13.138
                                            (8.0616)
pct_under_poverty_50                          0.0008
                                            (0.0006)
pct_work_from_home                            0.3484
                                            (0.2602)
======================== ============= =============
Effects                         Entity        Entity
                                  Time          Time
----------------------------------------------------

Std. Errors reported in parentheses
```