# CrimeRateAnalysisCode

December 11, 2022

[1]: # Import packages

```
import pandas as pd
    import numpy as np
    from sklearn.linear_model import LinearRegression
    from sklearn.preprocessing import PolynomialFeatures
    import matplotlib.pyplot as plt
    from sklearn.metrics import mean_squared_error
    from sklearn.preprocessing import normalize
    from matplotlib.pyplot import figure
     # from linearmodels import FamaMacBeth
    from sklearn.preprocessing import MinMaxScaler
    import statsmodels.formula.api as smf
    from scipy import stats
    import statsmodels.api as sm
    from sklearn.model_selection import KFold
    from sklearn.model_selection import cross_val_score
    from numpy import mean, std, absolute, sqrt
[2]: # Change this to run in your environment
    absolute_file_path = '~/Downloads/DMProjectRichaRishabh'
[3]: # check our accuracy for each degree, the lower the error the better!
    def fetch_best_degree_regression_model(city_data, normalize_original_data,__

¬for_our_model=True):
        number_degrees = [1,2,3,4,5,6]
        plt_mean_squared_error = []
         if normalize original data:
            y_values = city_data['Scaled_CrimeCount']
             if for our model:
                x_values = city_data.loc[:,['Gender_ratio', 'Scaled_Unemployment',_
      → 'Scaled_MedianIncomeRate', 'WorkforceCount', 'PercentNegativeUsers',
      else:
```

```
x_values = city_data.loc[:,['Gender_ratio', 'Scaled_Unemployment',_
      ⇔'Scaled_MedianIncomeRate']]
        else:
            y values = city data['Cul. Crime count']
            if for_our_model:
                x values = city data.loc[:,['Gender ratio', 'UnemploymentRate',,,
      →'MedianIncomeRate', 'WorkforceCount', 'PercentNegativeUsers', □
      else:
                x_values = city_data.loc[:,['Gender_ratio', 'UnemploymentRate',__
      for degree in number_degrees:
            poly_model = PolynomialFeatures(degree=degree)
            poly_x_values = poly_model.fit_transform(x_values)
            poly_model.fit(poly_x_values, y_values)
            regression_model = LinearRegression()
            regression_model.fit(poly_x_values, y_values)
            y_pred = regression_model.predict(poly_x_values)
            plt_mean_squared_error.append(mean_squared_error(y_values, y_pred,_
      ⇔squared=False))
        plt.scatter(number_degrees,plt_mean_squared_error, color="green")
        plt.plot(number_degrees,plt_mean_squared_error, color="red")
        plt.title("Polynomial Regression MSE at different degrees")
        plt.show()
          return number_degrees[plt_mean_squared_error.
      → index(min(plt_mean_squared_error))]
        return 2
[4]: # Plot normalized histogram for model coefficients. coeff_params: dict of_
     ⇔coefficients with values
    def plot_hist_for_model_coefficients(coeff_params, p_vals,__
      min_max_normalization=False, save_fig=False, city_name="", time_period=""):
        coeff_params_significant = {}
        for k, v in coeff params.items():
            if p_vals[i] <= 0.05:</pre>
                coeff_params_significant[k] = v
            i += 1
```

```
coeff_params_significant = dict(sorted(coeff_params_significant.items(),__
      ⇔key=lambda item: item[1], reverse=False))
         if min_max_normalization:
             scaler = MinMaxScaler()
             norm_coeff_values = scaler.fit_transform(pd.
      →DataFrame(coeff_params_significant, index=[0]))
             norm_coeff_values = [i[0] for i in norm_coeff_values]
         else:
             norm_coeff_values = list(dict(coeff_params_significant).values())
         coeff_vars = list(dict(coeff_params_significant).keys())
           figure(figsize=(10, 8), dpi=80)
         plt.barh(coeff vars, norm coeff values)
         plt.title("Attributes with significant p-values contributing towards crime⊔
      ⇒rate")
         plt.xlabel("Coefficient Values")
         plt.ylabel("Attributes")
         if save_fig:
             plt.savefig('{}_P_VAL_{}.png'.format(city_name, time_period),__

¬transparent=True, bbox_inches='tight')
         plt.show()
[5]: def remove_interaction_terms(items_list, indices):
         res = []
         for idx, ele in enumerate(items_list):
             if idx not in indices:
                 res.append(ele)
         return res
[6]: # Removing interaction terms with less p-val in LA
     # Parameters: x=transformed x, z=interaction variable names
     # Removing following variables from Polynomial Equation
     # 3: WorkforceCount
     # 7: Gender ratio 2
     # 10: Gender_ratio WorkforceCount
     # 11: Gender ratio PercentNegativeUsers
     # 12: Gender_ratio FavorOfDemocrats
     # 13: Gender ratio SearchCountForDepression
     # 14: UnemploymentRate ~2
     # 15: UnemploymentRate MedianIncomeRate
     # 17: UnemploymentRate PercentNegativeUsers
     # 18: UnemploymentRate FavorOfDemocrats
     # 19: UnemploymentRate SearchCountForDepression
     # 20: MedianIncomeRate^2
     # 22: MedianIncomeRate PercentNegativeUsers
     # 23: MedianIncomeRate FavorOfDemocrats
     # 24: MedianIncomeRate SearchCountForDepression
     # 25: WorkforceCount^2
```

```
# 28: WorkforceCount SearchCountForDepression
     # 30: PercentNegativeUsers FavorOfDemocrats
     # 31: PercentNegativeUsers SearchCountForDepression
     def remove_interaction_terms_for_LA(x, z):
         new_x_ = []
         interaction_terms_indices = [3, 7, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, ___
      →22, 23, 24, 25, 28, 30, 31]
         for item in x:
            temp = remove_interaction_terms(item, interaction_terms_indices)
            new_x_.append(temp)
         new x = pd.DataFrame(np.array(new x), columns=remove interaction_terms(z,_
      ⇔interaction_terms_indices))
         return new_x_
[7]: # Removing interaction terms with less p-val in NYC
     # Parameters: x=transformed x, z=interaction variable names
     # Removing following variables from Polynomial Equation
     # 1: UnemploymentRate
     # 6: SearchCountForDepression
     # 11: Gender_ratio PercentNegativeUsers
     # 13: Gender ratio SearchCountForDepression
     # 14: UnemploymentRate^2
     # 17: UnemploymentRate PercentNegativeUsers
     # 19: UnemploymentRate SearchCountForDepression
     # 21: MedianIncomeRate WorkforceCount
     # 22: MedianIncomeRate PercentNegativeUsers
     # 24: MedianIncomeRate SearchCountForDepression
     # 26: WorkforceCount PercentNegativeUsers
     # 28: WorkforceCount SearchCountForDepression
     # 30: PercentNegativeUsers FavorOfDemocrats
     # 31: PercentNegativeUsers SearchCountForDepression
     # 33: FavorOfDemocrats SearchCountForDepression
     # 34: SearchCountForDepression^2
     def remove_interaction_terms_for_NYC(x, z):
         new x = []
         interaction_terms_indices = [1, 6, 11, 13, 14, 17, 19, 21, 22, 24, 26, 28, U
      →30, 31, 33, 34]
         for item in x:
            temp = remove_interaction_terms(item, interaction_terms_indices)
            new_x_.append(temp)
         new_x_ = pd.DataFrame(np.array(new_x_), columns=remove_interaction_terms(z,_
      →interaction_terms_indices))
```

return new\_x\_

```
[8]: # Removing interaction terms with less p-val in CHICAGO
      # Parameters: x=transformed x, z=interaction variable names
     def remove_interaction_terms_for_CHICAGO(x, z):
         new_x_ = []
          interaction_terms_indices = [1, 8, 14, 17, 19, 22, 24, 26, 28, 29, 30, 31, ___
         for item in x:
             temp = remove interaction_terms(item, interaction_terms_indices)
             new_x_.append(temp)
         new_x_ = pd.DataFrame(np.array(new_x_), columns=remove_interaction_terms(z,_
       →interaction_terms_indices))
         return new_x_
 [9]: # Performs 10-cross validation on our dataset to find RMSE
     def perform_k_cross_validation(X, y):
         #define cross-validation method to use
          cv = KFold(n_splits=10, random_state=1, shuffle=True)
         #build multiple linear regression model
         model = LinearRegression()
         #use k-fold CV to evaluate model
          scores = cross_val_score(model, X, y, scoring='neg_mean_squared_error',
                                  cv=cv, n_jobs=-1)
          #return MSE, std
         return mean(absolute(scores)), std(absolute(scores))
[10]: # Ground Truth
     mse ground truth before covid, std ground truth before covid = {}, {}
     mse_ground_truth, std_ground_truth = {}, {}
     def regress_ground_truth(city_name, city_data, best_degree,__
       →normalize_original_data, poly_model, before_covid=False):
         lin_model_p_vals, poly_model_p_vals = [], []
         if normalize_original_data:
             y = city_data['Scaled_CrimeCount']
             x = city_data.loc[:,['Gender_ratio', 'Scaled_Unemployment',_
       else:
             y = city_data['Cul. Crime count']
```

x = city\_data.loc[:,['Gender\_ratio', 'UnemploymentRate',\_

```
X = sm.add_constant(x)
   lin_model = sm.OLS(y, X).fit()
   for attributeIndex in range (0, len(X.columns)):
        lin_model_p_vals.append(lin_model.pvalues[attributeIndex])
   lin_model_summary = lin_model.summary()
    if before covid:
        mse_ground_truth_before_covid[city_name],__
 std_ground_truth_before_covid[city_name] = perform_k_cross_validation(X, y)
       mse_ground_truth[city_name], std_ground_truth[city_name] =__
 →perform_k_cross_validation(X, y)
      linear model = LinearRegression()
#
      linear_model.fit(x, y)
      r_{sq}lm = linear_{model.score}(x, y)
      features = ['Intercept'] + ['Gender_ratio', 'Scaled_Unemployment', __
 → 'Scaled MedianIncomeRate']
      p_val_lm = get_p_val(linear_model, x, y, features)
   if poly_model:
       transformer = PolynomialFeatures(degree=best_degree, include_bias=False)
        x_ = transformer.fit_transform(x)
        x_ = pd.DataFrame(np.array(x_), columns=transformer.
 →get_feature_names_out())
       X = sm.add_constant(x_)
       poly_model = sm.OLS(list(y), X).fit()
        for attributeIndex in range (0, len(X.columns)):
            poly_model_p_vals.append(poly_model.pvalues[attributeIndex])
       poly_model_summary = poly_model.summary()
     poly_model = LinearRegression().fit(x_, y)
     r_sq_pm = poly_model.score(x_, y)
#
     features = ['Intercept'] + list(transformer.get_feature_names_out())
     p\_val\_pm = get\_p\_val(poly\_model, x\_, y, features)
   print("Ground Truth:\nLinear Model summary:\n {}".format(lin_model_summary))
     print("Model Coefficients: \nLinear: {}\n".format(list(linear model.
 ⇔coef )))
   print("\n\nPlot for Linear Model Coefficients for Ground Truth:\n")
   plot_hist_for_model_coefficients(lin_model.params, lin_model_p_vals)
      print("Polynomial: {}\n".format(list(poly_model.coef_)))
   if poly_model:
        print("\n\nPolynomial Model (degree={}) summary:\n {}\n".

¬format(best_degree, poly_model_summary))
       print("\n\nPlot for Polynormial Model Coefficients:\n")
       plot_hist_for_model_coefficients(poly_model.params, poly_model_p_vals)
```

```
[11]: # Our Model
            mse_our_model_before_covid, std_our_model_before_covid = {}, {}
            mse_our_model, std_our_model = {}, {}
            def regress_our_model(city_name, city_data, best_degree,_
               anormalize_original_data, include_mental_health_data, poly_model,_
               ⇔covid=False, before_covid=False, save_fig=False, time_period=""):
                     lin_model_p_vals, poly_model_p_vals = [], []
                     if normalize_original_data:
                              y = city_data['Scaled_CrimeCount']
                              if include_mental_health_data:
                                       ori_features = ['Gender_ratio', 'Scaled_Unemployment', _
                →'Scaled_MedianIncomeRate', 'WorkforceCount', 'PercentNegativeUsers', ⊔

¬'FavorOfDemocrats', 'Scaled_SearchCountForDepression']

                              else:
                                      ori_features = ['Gender_ratio', 'Scaled_Unemployment', _
               → 'Scaled_MedianIncomeRate', 'WorkforceCount', 'PercentNegativeUsers', ⊔
               elif include_mental_health_data:
                              y = city_data['Cul. Crime count']
                              ori_features = ['Gender_ratio', 'UnemploymentRate', 'MedianIncomeRate', unemploymentRate', unemploymentRate'
                →'WorkforceCount', 'PercentNegativeUsers', 'FavorOfDemocrats', □
               ⇔'SearchCountForDepression']
                     else:
                              y = city_data['Cul. Crime count']
                              ori_features = ['Gender_ratio', 'UnemploymentRate', 'MedianIncomeRate', u

¬'WorkforceCount', 'PercentNegativeUsers', 'FavorOfDemocrats']

                     if covid:
                              ori_features += ['CovidPercPositive']
                     x = city_data.loc[:,ori_features]
                     X = sm.add\_constant(x)
                     lin_model = sm.OLS(y, X).fit()
                     for attributeIndex in range (0, len(X.columns)):
                              lin_model_p_vals.append(lin_model.pvalues[attributeIndex])
                     lin_model_summary = lin_model.summary()
                     if not covid:
                              if before_covid:
                                      mse_our_model_before_covid[city_name],__
                std_our_model_before covid[city_name] = perform k_cross_validation(X, y)
                              else:
                                      mse_our_model[city_name], std_our_model[city_name] =_
               →perform_k_cross_validation(X, y)
                          linear_model = LinearRegression()
```

```
linear_model.fit(x, y)
     r_sq_lm = linear_model.score(x, y)
     features = ['Intercept'] + ori_features
     p_val_lm = get_p_val(linear_model, x, y, features)
    # poly = PolynomialFeatures(degree = 2)
   # X_poly = poly.fit_transform(x)
   # poly.fit(X_poly, y)
   # poly model = LinearRegression()
    # poly_model.fit(X_poly, y)
   \# r_sq_pm = poly_model.score(X_poly, y)
   if poly_model:
       transformer = PolynomialFeatures(degree=best_degree, include_bias=False)
       x_ = transformer.fit_transform(x)
       z = transformer.get_feature_names_out()
       if city_name == "LA" and not covid:
            x_ = remove_interaction_terms_for_LA(x_, z)
       elif city_name == "NYC" and not covid:
            x_ = remove_interaction_terms_for_NYC(x_, z)
       elif city_name == "CHICAGO" and not covid:
            x_ = remove_interaction_terms_for_CHICAGO(x_, z)
       else:
            x_ = pd.DataFrame(np.array(x_), columns=z)
       X = sm.add constant(x)
       poly_model = sm.OLS(list(y), X).fit()
       for attributeIndex in range (0, len(X.columns)):
            poly_model_p_vals.append(poly_model.pvalues[attributeIndex])
       poly_model_summary = poly_model.summary()
#
     poly_model = LinearRegression().fit(x_, y)
     r_sq_pm = poly_model.score(x_, y)
     features = ['Intercept'] + list(transformer.get_feature_names_out())
     p_val_pm = qet_p_val(poly_model, x_v, y_v, features)
   print("Our Model:\nLinear Model summary:\n {}".format(lin_model_summary))
     print("Model Coefficients: \nLinear: {}\n".format(list(linear_model.
⇔coef_)))
   print("\n\nPlot for Linear Model Coefficients for Our Model:\n")
   plot_hist_for_model_coefficients(lin_model.params, lin_model_p_vals)
     print("Polynomial: {}\n".format(list(poly_model.coef_)))
   if poly_model:
       print("\n\nPolynomial Model (degree={}) summary:\n {}\n".
 →format(best_degree, poly_model_summary))
       print("\n\nPlot for Polynormial Model Coefficients:\n")
       plot_hist_for_model_coefficients(poly_model.params, poly_model_p_vals)
```

```
[12]: # Our Model without ground truth columns
```

```
# mse our model before covid, std our model before covid = {}, {}
# mse_our_model, std_our_model = {}, {}
def regress_our_model_without_ground_truth(city_name, city_data,__
 ⊸normalize_original_data, include_mental_health_data, poly_model,_u
 $\text{\text{covid}=False, before_covid=False, save_fig=False, time_period=""}):
   lin_model_p_vals, poly_model_p_vals = [], []
   if normalize original data:
        y = city_data['Scaled_CrimeCount']
        if include_mental_health_data:
            ori_features = ['WorkforceCount', 'PercentNegativeUsers',_

¬'FavorOfDemocrats', 'Scaled_SearchCountForDepression']

            ori_features = ['WorkforceCount', 'PercentNegativeUsers',_
 elif include mental health data:
        y = city_data['Cul. Crime count']
        ori_features = ['WorkforceCount', 'PercentNegativeUsers',__

¬'FavorOfDemocrats', 'SearchCountForDepression']
   else:
        y = city data['Cul. Crime count']
        ori_features = ['WorkforceCount', 'PercentNegativeUsers',_
 if covid:
        ori_features += ['CovidPercPositive']
   x = city_data.loc[:,ori_features]
   X = sm.add\_constant(x)
   lin_model = sm.OLS(y, X).fit()
   for attributeIndex in range (0, len(X.columns)):
        lin_model_p_vals.append(lin_model.pvalues[attributeIndex])
   lin model summary = lin model.summary()
      if not covid:
#
          if before_covid:
              mse_our_model_before_covid[city_name],__
 std our model before covid[city name] = perform k cross validation(X, y)
              mse_our_model[city_name], std_our_model[city_name] =_
 \neg perform_k\_cross\_validation(X, y)
      linear_model = LinearRegression()
      linear_model.fit(x, y)
     r_{sq}lm = linear_{model.score}(x, y)
     features = ['Intercept'] + ori_features
     p_val_lm = get_p_val(linear_model, x, y, features)
```

```
# poly = PolynomialFeatures(degree = 2)
   # X_poly = poly.fit_transform(x)
   # poly.fit(X_poly, y)
  # poly_model = LinearRegression()
  # poly_model.fit(X_poly, y)
   \# r_sq_pm = poly_model.score(X_poly, y)
  if poly model:
      transformer = PolynomialFeatures(degree=best_degree, include_bias=False)
      x = transformer.fit transform(x)
      z = transformer.get_feature_names_out()
      if city name == "LA" and not covid:
           x_ = remove_interaction_terms_for_LA(x_, z)
       elif city name == "NYC" and not covid:
           x_ = remove_interaction_terms_for_NYC(x_, z)
       elif city_name == "CHICAGO" and not covid:
           x_ = remove_interaction_terms_for_CHICAGO(x_, z)
      else:
           x_ = pd.DataFrame(np.array(x_), columns=z)
      X = sm.add_constant(x_)
      poly_model = sm.OLS(list(y), X).fit()
      for attributeIndex in range (0, len(X.columns)):
           poly_model_p_vals.append(poly_model.pvalues[attributeIndex])
      poly_model_summary = poly_model.summary()
    poly\ model = LinearRegression().fit(x, y)
    r_sq_pm = poly_model.score(x_, y)
    features = ['Intercept'] + list(transformer.get feature names out())
    p\_val\_pm = get\_p\_val(poly\_model, x\_, y, features)
  print("Our Model without ground truth:\nLinear Model summary:\n {}".

→format(lin_model_summary))
    print("Model Coefficients: \nLinear: {}\n".format(list(linear_model.
⇔coef )))
  print("\n\nPlot for Linear Model Coefficients for Our Model without ground⊔
⇔truth:\n")
  plot_hist_for_model_coefficients(lin_model.params, lin_model_p_vals)
    print("Polynomial: {}\n".format(list(poly_model.coef_)))
  if poly_model:
      print("\n\nPolynomial Model (degree={}) summary:\n {}\n".

¬format(best_degree, poly_model_summary))
      print("\n\nPlot for Polynormial Model Coefficients:\n")
      plot_hist_for_model_coefficients(poly_model.params, poly_model_p_vals)
```

```
[13]: # Plot Correlation graphs

def plot_correlation_graphs(city_data, normalize_original_data):
    print("\nCorrelation Graphs:\n")
```

```
if normalize_original_data:
              unemployment_col = city_data['Scaled_Unemployment']
              median_income_col = city_data['Scaled_MedianIncomeRate']
              y = city_data['Scaled_CrimeCount']
          else:
              unemployment_col = city_data['UnemploymentRate']
              median_income_col = city_data['MedianIncomeRate']
              y = city_data['Cul. Crime count']
          figure(figsize=(15, 10), dpi=80)
          plt.subplot(2, 3, 1)
          plt.scatter(city_data['Gender_ratio'], y)
          plt.title("Gender Ratio v/s Crime Count")
          plt.subplot(2, 3, 2)
          plt.scatter(unemployment_col, y)
          plt.title("Scaled_Unemployment v/s Crime Count")
          plt.subplot(2, 3, 3)
          plt.scatter(median_income_col, y)
          plt.title("Scaled_MedianIncomeRate v/s Crime Count")
          plt.subplot(2, 3, 4)
          plt.scatter(city_data['WorkforceCount'], y)
          plt.title("WorkforceCount v/s Crime Count")
          plt.subplot(2, 3, 5)
          plt.scatter(city_data['PercentNegativeUsers'], y)
          plt.title("PercentNegativeUsers v/s Crime Count")
          plt.subplot(2, 3, 6)
          plt.scatter(city_data['FavorOfDemocrats'], y)
          plt.title("FavorOfDemocrats v/s Crime Count")
          plt.show()
[14]: # Append multiple city dataframes into single list
      # def build_single_dataset(city_name, city_data, all_cities_df):
            city_data['City'] = city_name
            all_cities_df.append(city_data)
[15]: # Min-Max Normalization on full data
      def normalize_dataset(city_data, include_mental_health_data):
          scaler = MinMaxScaler()
```

```
city_data[["Scaled_CrimeCount"]] = scaler.fit_transform(city_data[['Cul._
Crime count']])
  city_data[["Scaled_Unemployment"]] = scaler.
fit_transform(city_data[['UnemploymentRate']])
  city_data[["Scaled_MedianIncomeRate"]] = scaler.
fit_transform(city_data[['MedianIncomeRate']])
  if include_mental_health_data:
      city_data[["Scaled_SearchCountForDepression"]] = scaler.
fit_transform(city_data[['SearchCountForDepression']])
```

```
[16]: # Covid File Name Structure - <CityNameInCaps>_Covid.csv, No Header, First_
       ⇔Column as Percent and Second Column as MonthYear
      def infer_covid_comparison(city_name, city_data, absolute_file_path,_
       ⇒best_degree, normalize_original_data, include_mental_health_data, ⊔
       →poly_model):
          city_covid = pd.read_csv("{}}{}_Covid.csv".format(absolute_file_path,__
       ⇔city_name), header=None)
          city covid.columns = ['Perc', 'MonthYear']
          city_covid['MonthYear'] = pd.to_datetime(city_covid['MonthYear'],__
       city_covid = city_covid.sort_values(by=['MonthYear'])
         city_data['MonthYear'] = pd.to_datetime(city_data['MonthYear'],__

¬format="%b-%y")

         city_combined_dataset_covid = city_data[city_data['MonthYear'] >=__
       perc = []
         for index, row in city_combined_dataset_covid.iterrows():
             month_year = row['MonthYear']
             perc_pos_covid_cases = city_covid[city_covid['MonthYear'] ==__
       →month_year]['Perc']
             perc.append(float(perc_pos_covid_cases))
         city_combined_dataset_covid['CovidPercPositive'] = perc
         print("\nCovid Data Comparison:\n\nRegression from Mar-2020 to Dec-2021⊔
       →along with Covid Positive Cases Per Month:\n")
         regress_our_model(city_name, city_combined_dataset_covid, best_degree,_
       anormalize_original_data, include_mental_health_data, poly_model, covid=True)
         print("\nRegression for the same time frame without considering Covid Cases:
       \hookrightarrow \n''
         regress_our_model(city_name, city_combined_dataset_covid, best_degree,_
       normalize_original_data, include_mental_health_data, poly_model)
```

```
[17]: # File Name Structure - <CityNameInCaps> GoogleTrends.csv, with original file
       ⇔format as downloaded from google trends
      def add_mental_health_data(city_name, city_data, absolute_file_path):
          mh_data = pd.read_csv("{}/{}_GoogleTrends.csv".format(absolute_file_path,__
       ⇔city_name), header=1)
          mh_data['Month'] = pd.to_datetime(mh_data['Month'], format="%Y-%m")
          mh_data = mh_data.sort_values(by=['Month'])
          mh_data.columns = ['Month', 'Count']
          city_data['MonthYear'] = pd.to_datetime(city_data['MonthYear'],__

¬format="%b-%y")

          city_data = city_data.sort_values(by=['MonthYear'])
          city_data['SearchCountForDepression'] = list(mh_data['Count'])
            city_data.to_csv("{}-withMentalData.csv".format(city_name))
          return city_data
[18]: # For few cities, MonthYear Column was missing, so created on the fly
      def create_month_year_column(city_data):
          city_data['YearMonth'] = pd.to_datetime(city_data['YearMonth'],__

¬format="%y-%b")
          city_data["MonthYear"] = city_data['YearMonth'].dt.strftime("%b-%y")
          return city_data
[19]: def fetch_city_data_before_covid(city_data):
          city_data['Time'] = pd.to_datetime(city_data['MonthYear'], format="%b-%y")
          return city_data[city_data['Time'] < '2020-03-01']</pre>
[20]: def plot_time_series_graph(city_name, city_data, save_fig=False):
          plt.figure(figsize=(16, 8), dpi=150)
            city_data['WorkforceCount'].plot(label='Workforce%', color='orange')
            city data['Scaled CrimeCount'].plot(label='Crime%')
      #
            plt.title('{}-Workforce% v/s Crime%'.format(city_name))
           plt.xlabel('Time Period (Months) - 2011-2021')
      #
            plt.legend()
         fig, ax1 = plt.subplots()
          ax2 = ax1.twinx()
          ax1.plot(city_data["MonthYear"], city_data['Scaled_Unemployment'], 'g-',_
       ⇔color="#6495ED")
          ax2.plot(city_data["MonthYear"], city_data['Scaled_CrimeCount'], 'b-',__

color="#CC4F1B")

          ax1.set xlabel('Time Period (Months) - 2011-2021')
          ax1.set_ylabel('Unemployment%', color='#6495ED')
```

```
[21]: # Driver Function to read and process data for all cities
      def infer_data(city_name, city_file, all_cities_df, absolute file_path,_
       ⇔normalize_original_data=True, include_mental_health_data=True,⊔
       →poly_model=True):
          city_data = pd.read_csv("{}/{}".format(absolute_file_path, city_file),__
       →header=0)
          if city_name in ["SEATTLE", "DENVER", "DALLAS", "NEW_ORLEANS", "NYC"]:
              city_data = create_month_year_column(city_data)
          if include_mental_health_data:
              city_data = add_mental_health_data(city_name, city_data,__
       ⇒absolute_file_path)
          if normalize_original_data:
              normalize_dataset(city_data, include_mental_health_data)
            build_single_dataset(city_name, city_data, all_cities_df)
            print("\nMSE\ for\ different\ degree\ of\ Polynomials\ for\ Ground\ Truth:\n")
            best_degree_for_ground_truth =
       \hookrightarrow fetch_best_degree_regression_model(city_data, normalize_original_data,_u
       ⇔for_our_model=False)
            print("\nmse\ for\ different\ degree\ of\ Polynomials\ for\ Our\ Model:\n")
            best degree for our model = fetch best degree regression model (city data, ____
       \neg normalize\_original\_data)
          best_degree_for_ground_truth, best_degree_for_our_model = 0, 0
          print("\nBefore Covid (Mar-2020)\n\n")
          city_data_subset = fetch_city_data_before_covid(city_data)
          regress_ground_truth(city_name, city_data_subset,_
       ⇒best_degree_for_ground_truth, normalize_original_data, poly_model,_
       ⇔before_covid=True)
          regress_our_model(city_name, city_data_subset, best_degree_for_our_model,_u
       anormalize_original_data, include_mental_health_data, poly_model,__
       ⇔before_covid=True)
```

```
regress our model without ground truth(city name, city data,
onormalize original data, include mental health data, poly model,
sbefore_covid=True, save_fig=True, time_period="WithoutGroundTruth")
  print("\nTill Dec-2021\n\n")
  regress ground truth(city name, city data, best degree for ground truth,
→normalize_original_data, poly_model)
  regress our model(city name, city data, best_degree for our model, u
anormalize_original_data, include_mental_health_data, poly_model)
  regress our model without ground truth(city name, city data,,,
anormalize_original_data, include_mental_health_data, poly_model,_u
defore_covid=True, save_fig=True, time_period="WithoutGroundTruth")
  if city_name in ["LA", "CHICAGO", "NYC"]:
      infer_covid_comparison(city_name, city_data, absolute_file_path,_
→best_degree_for_our_model, normalize_original_data,
→include_mental_health_data, poly_model)
  plot_correlation_graphs(city_data, normalize_original_data)
  plot_time_series_graph(city_name, city_data, save_fig=True)
```

```
[22]: # Create Final Dataset including all cities and run regression
      # def infer final dataset all cities(all cities df):
            all_cities_final_dataset = pd.concat(all_cities_df)
            all cities final dataset['MonthYear'] = pd.
       •to_datetime(all_cities_final_dataset['MonthYear'], format="%b-%y")
            all_cities_final_dataset['CrimeCount'] = all_cities_final_dataset['Cul.__
       →Crime count']
            all\_cities\_final\_dataset = all\_cities\_final\_dataset.loc[:,['MonthYear', ]
       → 'City', 'CrimeCount', 'Gender_ratio', 'UnemploymentRate',
       → 'MedianIncomeRate', 'WorkforceCount', 'PercentNegativeUsers',
       → 'FavorOfDemocrats']]
            all_cities_final_dataset = all_cities_final_dataset.
       ⇔sort_values(by=['MonthYear', 'City'])
            all\_cities\_final\_dataset.to\_csv('final\_dataset.csv', index=False, \_
       \hookrightarrowheader=True)
            def ols_coef(x, formula):
                return smf.ols(formula,data=x).fit().params
```

```
qamma = (all_cities_final_dataset.groupby('MonthYear').
→apply(ols_coef, 'CrimeCount ~ 1 + Gender_ratio + UnemploymentRate +L
→MedianIncomeRate + WorkforceCount + PercentNegativeUsers +
→FavorOfDemocrats'))
     def fm_summary(p):
         s = p.describe().T
         s['std error'] = s['std']/np.sqrt(s['count'])
         s['tstat'] = s['mean']/s['std_error']
         return s[['mean','std_error','tstat']]
     print(fm_summary(qamma))
     all_cities_final_dataset = all_cities_final_dataset.set_index(['City',__
→ 'MonthYear'])
     print(all_cities_final_dataset)
     model = FamaMacBeth.from_formula('CrimeCount ~ 1 + Gender_ratio +
\hookrightarrow UnemploymentRate + MedianIncomeRate + WorkforceCount + PercentNegativeUsers_\sqcup
→+ FavorOfDemocrats', data=all_cities_final_dataset)
     result = model.fit(cov_type= 'kernel', debiased = False, bandwidth = 3)
     print(result.summary)
```

```
[23]: # Plot Side-by-side bar graph for MSE in both the models
      def plot_rmse(mse_our_model, std_our_model, mse_ground_truth, std_ground_truth, u
       ⇒before_covid=False):
          mse_our_model_values, std_our_model_values, mse_ground_truth_values,
       std_ground_truth_values = [], [], [], []
          for city in cities:
              mse_our_model_values.append(mse_our_model[city])
              std_our_model_values.append(std_our_model[city])
              mse_ground_truth_values.append(mse_ground_truth[city])
              std_ground_truth_values.append(std_ground_truth[city])
          x_indices = np.arange(len(cities)) # the x locations for the groups
                             # the width of the bars
          width = 0.35
          fig = plt.figure()
          ax = fig.add subplot(111)
          rects1 = ax.bar(x_indices, mse_ground_truth_values, width,__

¬color='lightblue', yerr=std_ground_truth_values)
          rects2 = ax.bar(x_indices+width, mse_our_model_values, width,__
       ⇔color='royalblue', yerr=std_our_model_values)
          # a.d.d. some.
          ax.set_ylabel('Mean Square Error')
```

```
[24]: # Main Initiating Code Block
      # cities_files = {'LA': 'CSV_LA_city_final_dataset_v2.csv','CHICAGO':__
      +'chicago\_city\_final\_dataset\_v2.csv','NYC': 'NYC\_final\_dataset\_v2.csv'\}
      cities = ["NYC", "LA", "CHICAGO", "NASHVILLE", "BOSTON", "SEATTLE", "DENVER",
       ⇔"DALLAS", "NEW_ORLEANS", "INDIANAPOLIS"]
      # cities = ["LA"]
      all_cities_df = []
      for city_name in cities:
          print("\n\n{}:\n".format(city_name))
          city_file = "{}_final_dataset2.csv".format(city_name)
          infer_data(city_name, city_file, all_cities_df, absolute_file_path,_
       →normalize_original_data=True, poly_model=False)
      print("\nBefore Covid (Mar-2020)\n\n")
      plot_rmse(mse_our_model_before_covid, std_our_model_before_covid,_u
       ⇒mse_ground_truth_before_covid, std_ground_truth_before_covid, __
       ⇒before covid=True)
      print("\nTill Dec-2021\n\n")
      plot_rmse(mse_our_model, std_our_model, mse_ground_truth, std_ground_truth)
      # infer_final_dataset_all_cities(all_cities_df)
```

NYC:

Before Covid (Mar-2020)

Ground Truth:

# Linear Model summary:

# OLS Regression Results

=======================================		=====		========		=======
Dep. Variable:	Scaled_Crime	Count	R-squa	red:		0.834
Model:		OLS	Adj. R	-squared:		0.829
Method:	Least So	uares	F-stat	istic:		177.7
Date:	Sun, 11 Dec	2022	Prob (	F-statistic):		3.32e-41
Time:	16:	45:20	Log-Li	kelihood:		119.19
No. Observations:		110	AIC:			-230.4
Df Residuals:		106	BIC:			-219.6
Df Model:		3				
Covariance Type:	nonr	obust				
=======================================		=====				
========						
	cc	ef	std err	t	P> t	[0.025
0.975]						
const	27.24	71	16.375	1.664	0.099	-5.218
59.712						
Gender_ratio	-50.76	75	31.349	-1.619	0.108	-112.919
11.384						
Scaled_Unemployment	0.53	84	0.173	3.109	0.002	0.195
0.882						
Scaled_MedianIncomeF	Rate -0.39	93	0.061	-6.541	0.000	-0.520
-0.278						
O		=====	Dl			1 010
Omnibus:		5.741		-Watson:		1.219
<pre>Prob(Omnibus): Skew:</pre>		0.000	-	-Bera (JB):		90.769 1.95e-20
	_	1.198				
Kurtosis:		6.750	Cond.	NO.		5.39e+03
		===	===			======

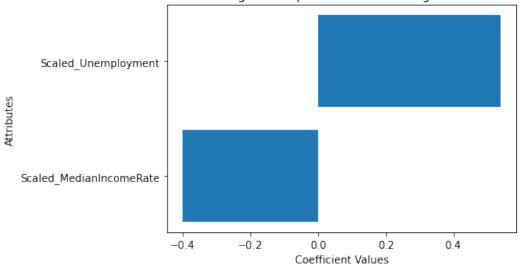
#### Notes

Plot for Linear Model Coefficients for Ground Truth:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 5.39e+03. This might indicate that there are strong multicollinearity or other numerical problems.





# Our Model:

OLS Regression Results

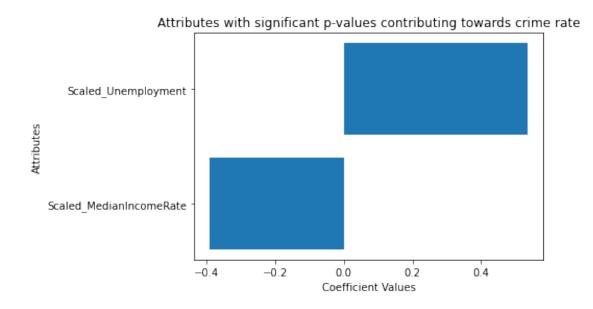
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.842		
Model:	OLS	Adj. R-squared:	0.831		
Method:	Least Squares	F-statistic:	77.80		
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	4.98e-38		
Time:	16:45:22	Log-Likelihood:	121.94		
No. Observations:	110	AIC:	-227.9		
Df Residuals:	102	BIC:	-206.3		
Df Model:	7				
Covariance Type:	nonrobust				
=======================================	=============				
=======================================					

	coef	std err	 t	P> t
[0.025 0.975]				
const	17.2737	44.739	0.386	0.700
-71.466 106.013				
Gender_ratio	-33.3607	88.219	-0.378	0.706
-208.343 141.621				
Scaled_Unemployment	0.5347	0.217	2.465	0.015
0.104 0.965				
Scaled_MedianIncomeRate	-0.3891	0.063	-6.224	0.000
-0.513 -0.265				
WorkforceCount	-7.6674	14.337	-0.535	0.594

-36.105	20.770					
PercentNegat	tiveUsers	-0.1	1104	0.135	-0.817	0.416
-0.378	0.158					
FavorOfDemo	crats	1.5	5674	2.028	0.773	0.441
-2.454	5.589					
Scaled_Sear	${\tt chCountForDepression}$	on 0.0	0834	0.047	1.778	0.078
-0.010	0.176					
========						
Omnibus:		32.899	Durbi	n-Watson:		1.254
Prob(Omnibus	s):	0.000	Jarqu	e-Bera (JB)	:	75.456
Skew:		-1.142	Prob(	JB):		4.12e-17
Kurtosis:		6.353	Cond.	No.		1.94e+04
=========		=======		========	========	========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.94e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

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OLS Regression Results

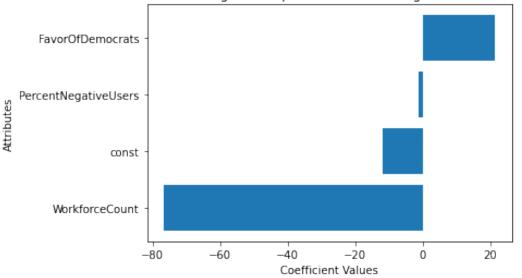
Dep. Variable: Scaled\_CrimeCount R-squared: 0.438

Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	OLS Least Squares Sun, 11 Dec 2022 16:45:22 132 127 4 nonrobust	F-st Prob Log- AIC: BIC:		c):	0.420 24.72 3.80e-15 29.632 -49.26 -34.85
[0.025 0.975]		coef	std err	t	P> t
const	-11.	9249	2.214	-5.386	0.000
-16.306 -7.543					
WorkforceCount	-76.	7194	9.522	-8.057	0.000
-95.561 -57.878					
PercentNegativeUsers	-1.	2691	0.296	-4.293	0.000
-1.854 -0.684	0.4	F000	0.005	4 070	0.000
FavorOfDemocrats 15.404 27.614	21.	5093	3.085	6.972	0.000
Scaled_SearchCountFo	rDoprossion -0	1112	0.089	-1.251	0.213
-0.287 0.065	TDepression -0.	1113	0.009	-1.251	0.213
				=======	
Omnibus: Prob(Omnibus):	18.806		in-Watson:		0.460
Skew:	0.000	-	ue-Bera (JB)	•	25.765 2.54e-06
Kurtosis:	4.521		. No.		764.
=======================================	=======================================	=====	 ========		:=======

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

Plot for Linear Model Coefficients for Our Model without ground truth:

# Attributes with significant p-values contributing towards crime rate



# Till Dec-2021

Ground Truth:

Linear Model summary:

# OLS Regression Results

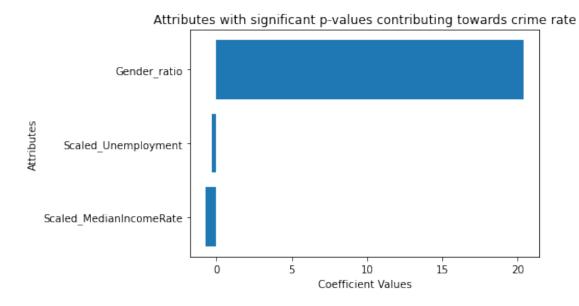
Dep. Variable:	Scaled_CrimeCount	R-squ	ared:		0.885
Model:	OLS	Adj.	R-squared:		0.882
Method:	Least Squares	F-sta	tistic:		327.8
Date:	Sun, 11 Dec 2022	Prob	(F-statistic):		7.19e-60
Time:	16:45:22	Log-L	ikelihood:		134.28
No. Observations:	132	AIC:			-260.6
Df Residuals:	128	BIC:			-249.0
Df Model:	3				
Covariance Type:	nonrobust				
=======================================	=============		=========		========
========					
	coef	std err	t	P> t	[0.025
0.975]					
const	-9.7313	5.039	-1.931	0.056	-19.702
0.240					
Gender_ratio	20.3820	9.620	2.119	0.036	1.347
Gender_ratio 39.417	20.3820	9.620	2.119	0.036	1.347

-0	1	22	
-0		$\omega_{z}$	

Scaled_MedianIncomeRate -0.629	-0.6854	0.028 -24.075	0.000 -0.742
Omnibus:	31.872	Durbin-Watson:	1.179
Prob(Omnibus):	0.000	<pre>Jarque-Bera (JB):</pre>	74.247
Skew:	-0.964	<pre>Prob(JB):</pre>	7.54e-17
Kurtosis:	6.128	Cond. No.	1.76e+03

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.76e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Ground Truth:



Our Model: Linear Model summary:

### OLS Regression Results

Dep. Variable:	Scaled_CrimeCount	R-squared:	0.890
Model:	OLS	Adj. R-squared:	0.884
Method:	Least Squares	F-statistic:	143.6
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	2.41e-56
Time:	16:45:22	Log-Likelihood:	137.43

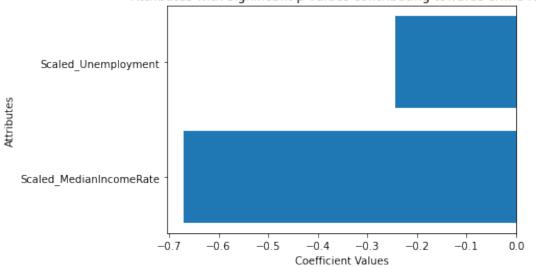
Covariance Type: nonrobust	No. Observations: Df Residuals:	132 124	AIC: BIC:			-258.9 -235.8
coef std err t P> t   [0.025 0.975]	Df Model:	7				
Coef   std err   t   P> t	Covariance Type: non	robust				
[0.025	=======================================	=====	======	=======		========
const -5.9746 5.525 -1.081 0.282 -16.911 4.961  Gender_ratio 11.5131 10.661 1.080 0.282 -9.589 32.615  Scaled_Unemployment -0.2438 0.048 -5.101 0.000 -0.338 -0.149  Scaled_MedianIncomeRate -0.6702 0.033 -20.346 0.000 -0.735 -0.605  WorkforceCount -7.3509 5.573 -1.319 0.190 -18.381 3.679  PercentNegativeUsers -0.2464 0.140 -1.760 0.081 -0.524 0.031  FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044  Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137			coef	std err	t	P> t
-16.911	[0.025 0.975]					
-16.911						
Gender_ratio		-5.	9746	5.525	-1.081	0.282
-9.589 32.615 Scaled_Unemployment -0.2438 0.048 -5.101 0.000 -0.338 -0.149 Scaled_MedianIncomeRate -0.6702 0.033 -20.346 0.000 -0.735 -0.605 WorkforceCount -7.3509 5.573 -1.319 0.190 -18.381 3.679 PercentNegativeUsers -0.2464 0.140 -1.760 0.081 -0.524 0.031 FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044 Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137						
Scaled_Unemployment       -0.2438       0.048       -5.101       0.000         -0.338       -0.149       -0.6702       0.033       -20.346       0.000         Scaled_MedianIncomeRate       -0.6702       0.033       -20.346       0.000         -0.735       -0.605       -0.605       -0.573       -1.319       0.190         -18.381       3.679       -0.2464       0.140       -1.760       0.081         -0.524       0.031       -0.031       -1.709       0.972       0.333         -1.722       5.044       5.044       0.042       1.258       0.211         -0.031       0.137	_	11.	5131	10.661	1.080	0.282
-0.338 -0.149 Scaled_MedianIncomeRate -0.6702 0.033 -20.346 0.000 -0.735 -0.605 WorkforceCount -7.3509 5.573 -1.319 0.190 -18.381 3.679 PercentNegativeUsers -0.2464 0.140 -1.760 0.081 -0.524 0.031 FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044 Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137						
Scaled_MedianIncomeRate       -0.6702       0.033       -20.346       0.000         -0.735       -0.605         WorkforceCount       -7.3509       5.573       -1.319       0.190         -18.381       3.679         PercentNegativeUsers       -0.2464       0.140       -1.760       0.081         -0.524       0.031         FavorOfDemocrats       1.6608       1.709       0.972       0.333         -1.722       5.044         Scaled_SearchCountForDepression       0.0531       0.042       1.258       0.211         -0.031       0.137         ====================================		-0.	2438	0.048	-5.101	0.000
-0.735 -0.605 WorkforceCount -7.3509 5.573 -1.319 0.190 -18.381 3.679 PercentNegativeUsers -0.2464 0.140 -1.760 0.081 -0.524 0.031 FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044 Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137						
WorkforceCount -7.3509 5.573 -1.319 0.190 -18.381 3.679 PercentNegativeUsers -0.2464 0.140 -1.760 0.081 -0.524 0.031 FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044 Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137	<del>-</del>	-0.	6702	0.033	-20.346	0.000
-18.381 3.679  PercentNegativeUsers -0.2464 0.140 -1.760 0.081 -0.524 0.031  FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044  Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137	******					
PercentNegativeUsers -0.2464 0.140 -1.760 0.081 -0.524 0.031 FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044 Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137 -0.031 0.		-7.	3509	5.573	-1.319	0.190
-0.524 0.031 FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044 Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137						
FavorOfDemocrats 1.6608 1.709 0.972 0.333 -1.722 5.044 Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137	•	-0.	2464	0.140	-1.760	0.081
-1.722 5.044 Scaled_SearchCountForDepression 0.0531 0.042 1.258 0.211 -0.031 0.137						
Scaled_SearchCountForDepression       0.0531       0.042       1.258       0.211         -0.031       0.137         ====================================		1.	6608	1.709	0.972	0.333
-0.031 0.137						
Omnibus: 31.465 Durbin-Watson: 1.200		0.	0531	0.042	1.258	0.211
Omnibus: 31.465 Durbin-Watson: 1.200						
						1 200
Prob(Omnibus): 0.000 Jarque-Bera (JB): 75.290	Prob(Omnibus):					75.290
Skew: -0.940 Prob(JB): 4.48e-17			-		•	
Kurtosis: 6.187 Cond. No. 2.47e+03						

Plot for Linear Model Coefficients for Our Model:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 2.47e+03. This might indicate that there are strong multicollinearity or other numerical problems.





Our Model without ground truth: Linear Model summary:

OLS Regression Results

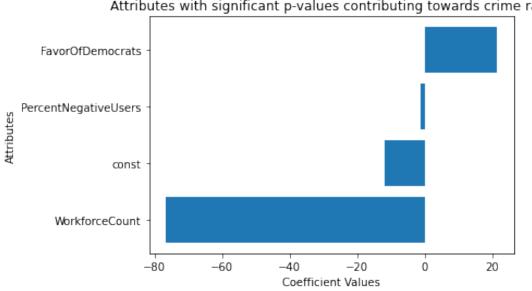
=============	========	=====		========		========
Dep. Variable:	Scaled_CrimeC	ount	R-sq	uared:		0.438
Model:		OLS	Adj.	R-squared:		0.420
Method:	Least Squ	ares	F-st	atistic:		24.72
Date:	Sun, 11 Dec	2022	Prob	(F-statistic	:):	3.80e-15
Time:	16:4	5:22	Log-	Likelihood:		29.632
No. Observations:		132	AIC:			-49.26
Df Residuals:		127	BIC:			-34.85
Df Model:		4				
Covariance Type:	nonro	bust				
=======================================	========	=====	=====	========		========
=======================================						<b>5</b> . 1. 1
[0 005 0 075]		(	coef	std err	t	P> t
[0.025 0.975]						
const		-11.9	9249	2.214	-5.386	0.000
-16.306 -7.543						
WorkforceCount		-76.7	7194	9.522	-8.057	0.000
-95.561 -57.878						
PercentNegativeUser	S	-1.2	2691	0.296	-4.293	0.000
-1.854 -0.684						
FavorOfDemocrats		21.5	5093	3.085	6.972	0.000
15.404 27.614						
Scaled_SearchCountF	orDepression	-0.1	1113	0.089	-1.251	0.213

#### -0.287 0.065

Omnibus:	18.806	Durbin-Watson:	0.460
Prob(Omnibus):	0.000	Jarque-Bera (JB):	25.765
Skew:	0.770	Prob(JB):	2.54e-06
Kurtosis:	4.521	Cond. No.	764.

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

Plot for Linear Model Coefficients for Our Model without ground truth:



Attributes with significant p-values contributing towards crime rate

# Covid Data Comparison:

Regression from Mar-2020 to Dec-2021 along with Covid Positive Cases Per Month:

# Our Model:

OLS Regression Results

Dep. Variable:	Scaled_CrimeCount	R-squared:	0.568
Model:	OLS	Adj. R-squared:	0.432
Method:	Least Squares	F-statistic:	4.200

Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	non	:45:23 22 16 5 robust	Log-AIC:	(F-statisti Likelihood:		0.0125 39.654 -67.31 -60.76
=======================================						
[0.025 0.975]		C	coef	std err	t	P> t
Gender_ratio		1.0	775	0.748	1.440	0.169
-0.508 2.663						
${\tt Scaled\_Unemployment}$		-0.1	.864	0.063	-2.954	0.009
-0.320 -0.053						
Scaled_MedianIncomeRa	ate	-0.7	'378	0.819	-0.901	0.381
-2.475 0.999						
WorkforceCount		-0.0	758	0.071	-1.067	0.302
-0.226 0.075						
PercentNegativeUsers		-1.5	430	0.834	-1.850	0.083
-3.311 0.225		4 6	000	0.005	4 470	0.450
FavorOfDemocrats		1.3	3225	0.895	1.478	0.159
-0.575 3.220	Donmoggion	0 1	E10	0.084	1.802	0.090
Scaled_SearchCountFor	Depression	0.1	.518	0.004	1.002	0.090
CovidPercPositive		-0.2	757	0.148	-1.859	0.082
-0.590 0.039		0.2	.101	0.140	1.009	0.002
=======================================		======	.====	========	=======	
Omnibus:		0.969	Durb	in-Watson:		2.645
Prob(Omnibus):		0.616	Jarq	ue-Bera (JB)	:	0.409
Skew:		0.334	-	(JB):		0.815
Kurtosis:		3.027	Cond	. No.		5.73e+17
=======================================		======	=====			

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The smallest eigenvalue is 1.41e-34. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

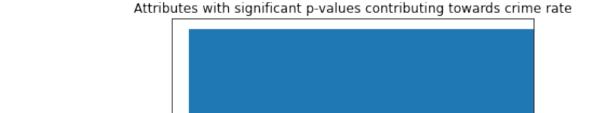
Plot for Linear Model Coefficients for Our Model:

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1807615713.py:1
9: 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 city\_combined\_dataset\_covid['CovidPercPositive'] = perc



Scaled\_Unemployment -

-0.175 -0.150 -0.125 -0.100 -0.075 -0.050 -0.025 0.000 Coefficient Values

Regression for the same time frame without considering Covid Cases:

### Our Model:

Linear Model summary:

# OLS Regression Results

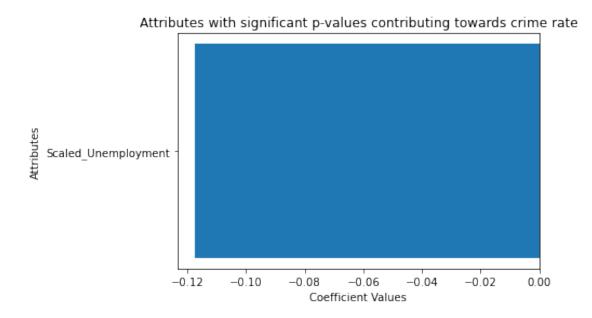
============			=====	========
Dep. Variable:	Scaled_CrimeCount	R-squared:		0.474
Model:	OLS	Adj. R-squared:		0.350
Method:	Least Squares	F-statistic:		3.833
Date:	Sun, 11 Dec 2022	Prob (F-statistic):		0.0213
Time:	16:45:23	Log-Likelihood:		37.503
No. Observations:	22	AIC:		-65.01
Df Residuals:	17	BIC:		-59.55
Df Model:	4			
Covariance Type:	nonrobust			
=======================================	:==========		=====	========
=======================================	=			
		coef std err	t	P> t
[0.025 0.975]				
[0.025 0.975]				

\_\_\_\_\_\_

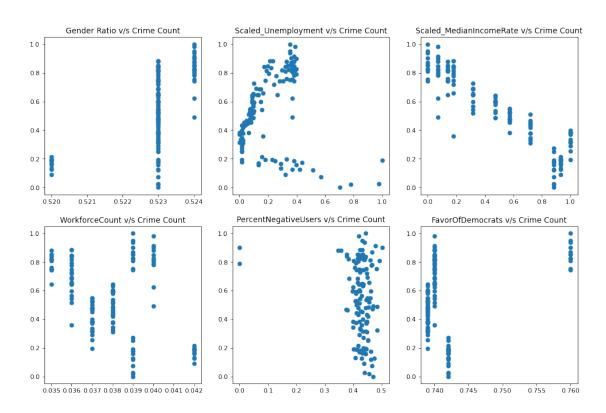
Gender_ratio		0.5	494	0.740	0.742	0.468
-1.012	2.111					
Scaled_Uner	nployment	-0.1	175	0.055	-2.151	0.046
-0.233	-0.002					
Scaled_Medi	ianIncomeRate	-0.1	462	0.808	-0.181	0.858
-1.850	1.558					
WorkforceCo	ount	-0.0	246	0.070	-0.351	0.730
-0.172	0.123					
PercentNega	ativeUsers	-1.1	112	0.857	-1.297	0.212
-2.919	0.696					
FavorOfDemocrats		0.6929		0.886	0.782	0.445
-1.177	2.563					
${\tt Scaled\_SearchCountForDepression}$		0.0247		0.053	0.469	0.645
-0.086	0.136					
Omnibus:		2.053	Durbin	-Watson:		2.341
Prob(Omnibu	ıs):	0.358	Jarque	-Bera (JB)	:	0.899
Skew:		0.465	Prob(J	B):		0.638
Kurtosis:		3.342	Cond.	No.		2.97e+18

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The smallest eigenvalue is 5.23e-36. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Plot for Linear Model Coefficients for Our Model:



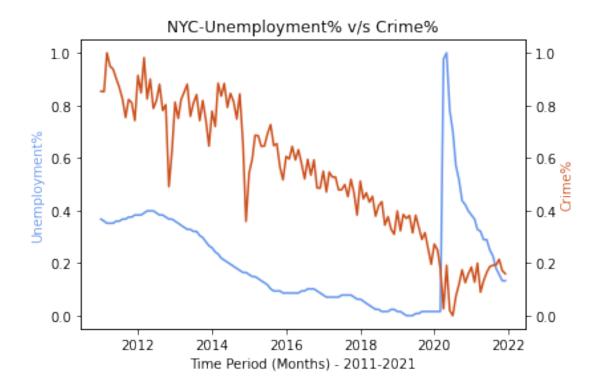
### Correlation Graphs:



/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



# LA:

Before Covid (Mar-2020)

Ground Truth:

Linear Model summary:

# OLS Regression Results

Dep. Variable:	Scaled_CrimeCount	R-squared:	0.864		
Model:	OLS	Adj. R-squared:	0.860		
Method:	Least Squares	F-statistic:	224.9		
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	8.48e-46		
Time:	16:45:23	Log-Likelihood:	119.41		
No. Observations:	110	AIC:	-230.8		
Df Residuals:	106	BIC:	-220.0		
Df Model:	3				
Covariance Type:	nonrobust				
=======================================					
========					

 $\texttt{coef} \qquad \texttt{std err} \qquad \qquad \texttt{t} \qquad \texttt{P>|t|} \qquad \texttt{[0.025]}$ 

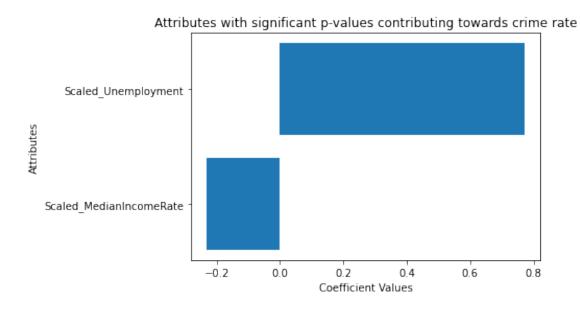
# 0.975]

const	-0.2077	2.189	-0.095	0.925	-4.547
4.132					
Gender_ratio	1.3841	4.296	0.322	0.748	-7.134
9.902					
Scaled_Unemployment	0.7707	0.108	7.155	0.000	0.557
0.984	0.0200	0 005	2 500	0.001	0.250
Scaled_MedianIncomeRate	-0.2302	0.065	-3.562	0.001	-0.358
-0.102					
Omnibus:	0.714	Durbin-	Watson:		1.177
Prob(Omnibus):	0.700	Jarque-	Bera (JB):		0.312
Skew:	0.049	Prob(JB):			0.856
Kurtosis:	3.242	Cond. N	ο.		725.
=======================================	=========	=======	========	========	=======

# Notes:

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

Plot for Linear Model Coefficients for Ground Truth:



# Our Model:

OLS Regression Results

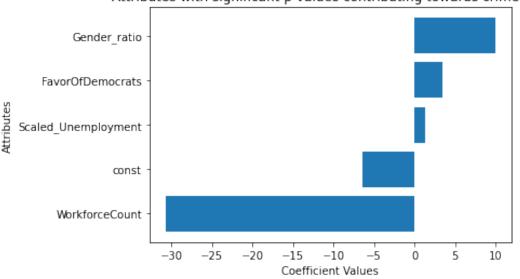
coef std err t P> t   [0.025	Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Scaled_CrimeCount OLS Least Squares Sun, 11 Dec 2022 16:45:23 110 102 7 nonrobust	Adj. F-st Prob			0.890 0.883 118.5 4.75e-46 131.23 -246.5 -224.8
const       -6.4065       2.537       -2.525       0.013         -11.438       -1.375       9.9219       4.337       2.287       0.024         1.319       18.525       1.2847       0.145       8.869       0.000         0.997       1.572       1.572       1.409       0.162         -0.247       0.042       0.042       0.073       -1.409       0.162         -43.544       -17.818       -17.818       -4.731       0.000         -43.544       -17.818       0.0555       0.063       0.880       0.381         -0.070       0.181       0.000			coef	std err	t	P> t
-11.438 -1.375  Gender_ratio 9.9219 4.337 2.287 0.024 1.319 18.525  Scaled_Unemployment 1.2847 0.145 8.869 0.000 0.997 1.572  Scaled_MedianIncomeRate -0.1025 0.073 -1.409 0.162 -0.247 0.042  WorkforceCount -30.6813 6.485 -4.731 0.000 -43.544 -17.818  PercentNegativeUsers 0.0555 0.063 0.880 0.381 -0.070 0.181  FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620  Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172						
Gender_ratio 9.9219 4.337 2.287 0.024 1.319 18.525 Scaled_Unemployment 1.2847 0.145 8.869 0.000 0.997 1.572 Scaled_MedianIncomeRate -0.1025 0.073 -1.409 0.162 -0.247 0.042 WorkforceCount -30.6813 6.485 -4.731 0.000 -43.544 -17.818 PercentNegativeUsers 0.0555 0.063 0.880 0.381 -0.070 0.181 FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620 Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172		-6.	4065	2.537	-2.525	0.013
1.319 18.525 Scaled_Unemployment 1.2847 0.145 8.869 0.000 0.997 1.572 Scaled_MedianIncomeRate -0.1025 0.073 -1.409 0.162 -0.247 0.042 WorkforceCount -30.6813 6.485 -4.731 0.000 -43.544 -17.818 PercentNegativeUsers 0.0555 0.063 0.880 0.381 -0.070 0.181 FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620 Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172		2	0040	4 007	0.007	0.004
Scaled_Unemployment       1.2847       0.145       8.869       0.000         0.997       1.572       0.073       -1.409       0.162         -0.247       0.042       0.042       0.0813       6.485       -4.731       0.000         -43.544       -17.818       0.0555       0.063       0.880       0.381         -0.070       0.181       0.063       0.080       0.003         1.173       5.620       0.0823       0.045       1.817       0.072         -0.008       0.172       0.172       0.0823       0.045       1.817       0.072	<del>-</del>	9.	9219	4.337	2.281	0.024
0.997 1.572 Scaled_MedianIncomeRate -0.1025 0.073 -1.409 0.162 -0.247 0.042 WorkforceCount -30.6813 6.485 -4.731 0.000 -43.544 -17.818 PercentNegativeUsers 0.0555 0.063 0.880 0.381 -0.070 0.181 FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620 Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172		1.	2847	0.145	8.869	0.000
-0.247 0.042 WorkforceCount -30.6813 6.485 -4.731 0.000 -43.544 -17.818 PercentNegativeUsers 0.0555 0.063 0.880 0.381 -0.070 0.181 FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620 Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172	- • •			0.110	0.000	
WorkforceCount -30.6813 6.485 -4.731 0.000 -43.544 -17.818  PercentNegativeUsers 0.0555 0.063 0.880 0.381 -0.070 0.181  FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620  Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172	Scaled_MedianIncome	Rate -0.	1025	0.073	-1.409	0.162
-43.544 -17.818  PercentNegativeUsers 0.0555 0.063 0.880 0.381 -0.070 0.181  FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620  Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172	-0.247 0.042					
PercentNegativeUsers 0.0555 0.063 0.880 0.381 -0.070 0.181  FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620  Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172			6813	6.485	-4.731	0.000
-0.070 0.181 FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620 Scaled_SearchCountForDepression 0.0823 0.045 1.817 0.072 -0.008 0.172						
FavorOfDemocrats 3.3964 1.121 3.029 0.003 1.173 5.620	_	s 0.	0555	0.063	0.880	0.381
1.173		3	3964	1.191	3.029	0.003
Scaled_SearchCountForDepression		0.	JJ J I	1.121	0.020	0.000
-0.008 0.172		orDepression 0.	0823	0.045	1.817	0.072
Omnibus: 3.685 Durbin-Watson: 1.2						1.202
					:	3.051
•				•		0.217
						1.48e+03

Plot for Linear Model Coefficients for Our Model:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 1.48e+03. This might indicate that there are strong multicollinearity or other numerical problems.





Our Model without ground truth:

OLS Regression Results

		=====			=======	========
Dep. Variable:	Scaled_Crime	Count	R-sqı	uared:		0.575
Model:		OLS	Adj.	R-squared:		0.562
Method:	Least Sq	uares	F-sta	atistic:		43.04
Date:	Sun, 11 Dec	2022	Prob	(F-statistic	:	8.83e-23
Time:	16:	45:24	Log-I	Likelihood:		41.755
No. Observations:		132	AIC:			-73.51
Df Residuals:		127	BIC:			-59.10
Df Model:		4				
Covariance Type:	nonr	obust				
=======================================	========	=====			=======	
=======================================	=					
		(	coef	std err	t	P> t
[0.025 0.975]						
	-	0 (	0421	0.054	8.429	0.000
const		8.0	J421	0.954	8.429	0.000
6.154 9.930		20. (	2006	0.046	2 440	0.000
WorkforceCount		-30.9	9226	9.846	-3.140	0.002
-50.407 -11.438			2500	0 445	4 750	
PercentNegativeUser	îs.	-0.2	2529	0.145	-1.750	0.083
-0.539 0.033		_				
FavorOfDemocrats		-9.4	4381	1.518	-6.216	0.000
-12.443 -6.433						
Scaled_SearchCountH	ForDepression	-0.3	1676	0.086	-1.939	0.055

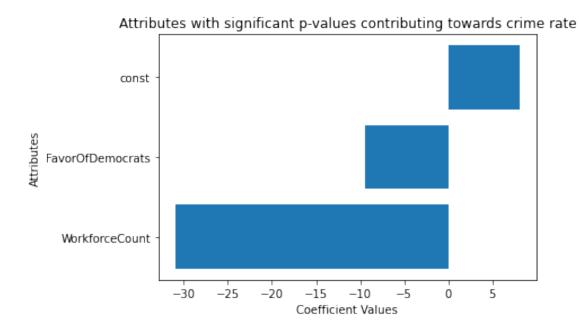
# -0.339 0.003

Omnibus:	5.613	Durbin-Watson:	0.417
Prob(Omnibus):	0.060	Jarque-Bera (JB):	2.849
Skew:	-0.048	Prob(JB):	0.241
Kurtosis:	2.287	Cond. No.	873.

#### Notes:

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

Plot for Linear Model Coefficients for Our Model without ground truth:



Till Dec-2021

### Ground Truth:

OLS Regression Results

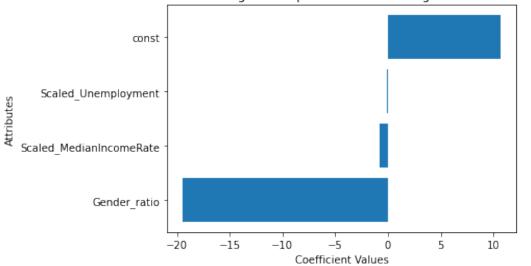
===========			=========
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.857
Model:	OLS	Adj. R-squared:	0.854
Method:	Least Squares	F-statistic:	256.3

Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Sun,	11 Dec 2022 16:45:24 132 128 nonrobust	Log-L AIC: BIC:	(F-statistic): ikelihood:		6.51e-54 113.70 -219.4 -207.9
=======		coef	std err	 t	P> t	[0.025
0.975]						
const		10.6498	2.114	5.037	0.000	6.466
14.834						
Gender_ratio -11.153		-19.4411	4.189	-4.641	0.000	-27.730
Scaled_Unemployment -0.017		-0.1041	0.044	-2.376	0.019	-0.191
Scaled_MedianIncomeRa-0.694	ate	-0.7496	0.028	-26.773	0.000	-0.805
Omnibus:	=====	 0.100	======= ) Durbi	======== n-Watson:	=======	0.969
Prob(Omnibus):		0.951	l Jarqu	e-Bera (JB):		0.239
Skew:		0.046	B Prob(	JB):		0.887
Kurtosis:		2.813	Cond.	No.		642.
			===			=======

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

Plot for Linear Model Coefficients for Ground Truth:





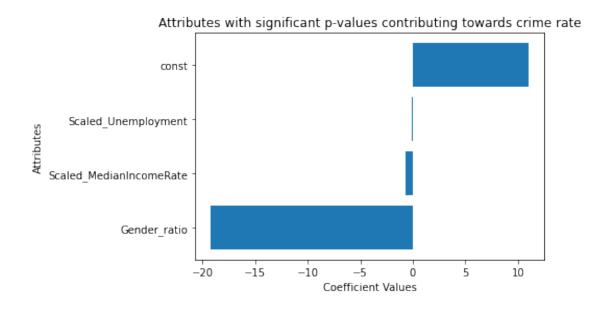
Our Model: Linear Model summary:

=======================================							
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals:	OLS Least Squares Sun, 11 Dec 2022	Adj. F-sta Prob Log-I	R-squared: atistic:	ic):	0.858 0.850 107.1 1.78e-49 114.08 -212.2 -189.1		
Df Model:	7	DIO.			100.1		
Covariance Type:	nonrobust						
[0.025 0.975]		====== coef		t	P> t		
const 6.390 15.575	10.	9824	2.320	4.733	0.000		
Gender_ratio -10.614		1958	4.336	-4.428	0.000		
Scaled_Unemployment -0.239 -0.017		1280	0.056	-2.282	0.024		
Scaled_MedianIncome -0.837 -0.646	Rate -0.	7417	0.048	-15.383	0.000		
WorkforceCount	4.	4923	6.928	0.648	0.518		

-9.221	18.205					
PercentNegat	civeUsers	-0.0	257	0.086	-0.299	0.765
-0.195	0.144					
FavorOfDemod	crats	-0.7	881	1.234	-0.638	0.524
-3.231	1.655					
Scaled_Searc	${\tt chCountForDepression}$	0.0	128	0.053	0.242	0.809
-0.092	0.117					
Omnibus:		0.103	Durbin-	Watson:		0.980
Prob(Omnibus	3):	0.950	Jarque-	Bera (JB	):	0.173
Skew:		0.065	Prob(JB	3):		0.917
Kurtosis:		2.879	Cond. N	o.		1.19e+03
=========		======	======	======	========	========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.19e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

OLS Regression Results

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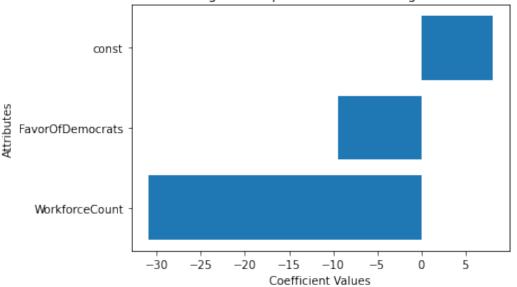
Dep. Variable: Scaled\_CrimeCount R-squared: 0.575

Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	132 127 4 nonrobust	F-st Prob Log- AIC: BIC:	(F-statisti Likelihood:	.c):	0.562 43.04 8.83e-23 41.755 -73.51 -59.10
[0.025 0.975]		coef	std err	t	P> t
const	8.	0421	0.954	8.429	0.000
6.154 9.930					
WorkforceCount	-30.	9226	9.846	-3.140	0.002
-50.407 -11.438					
PercentNegativeUsers	-0.	2529	0.145	-1.750	0.083
-0.539 0.033	0	4004	4 540	6 046	0.000
FavorOfDemocrats -12.443 -6.433	-9.	4381	1.518	-6.216	0.000
Scaled_SearchCountFo	urDenression -0	1676	0.086	-1.939	0.055
-0.339 0.003	iDepression 0.	1070	0.000	1.959	0.000
	 5.613		======== oin-Watson:		0.417
Prob(Omnibus):			ue-Bera (JB)	•	2.849
Skew:	-0.048	-	•	•	0.241
Kurtosis:	2.287		l. No.		873.
					=======

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

Plot for Linear Model Coefficients for Our Model without ground truth:

# Attributes with significant p-values contributing towards crime rate



## Covid Data Comparison:

Regression from Mar-2020 to Dec-2021 along with Covid Positive Cases Per Month:

## Our Model:

Linear Model summary:

Dep. Variable:	Scaled_CrimeCount	R-squared:		0.256
Model:	OLS	Adj. R-squared:		0.024
Method:	Least Squares	F-statistic:		1.101
Date:	Sun, 11 Dec 2022	Prob (F-statisti	.c):	0.398
Time:	16:45:24	Log-Likelihood:		33.988
No. Observations:	22	AIC:		-55.98
Df Residuals:	16	BIC:		-49.43
Df Model:	5			
Covariance Type:	nonrobust			
===========				
	,	coef std err	t	P> t
[0.025 0.975]	•	coef std err	t	P> t
[0.025 0.975]		coef std err	t	P> t
[0.025 0.975]		coef std err	t	P> t
		coef std err	t  0.145	P> t  
[0.025 0.975]			·	
Gender_ratio -0.574 0.658	0.0		0.145	0.887
Gender_ratio	0.0	0420 0.291	·	

-0.114	0.167					
Scaled_Medi	anIncomeRate	0.1	.545	0.211	0.731	0.475
-0.293	0.602					
WorkforceCo	unt	0.0	026	0.011	0.234	0.818
-0.021	0.026					
PercentNega	tiveUsers	-0.2	.587	0.639	-0.405	0.691
-1.612	1.095					
FavorOfDemo	crats	0.0	614	0.393	0.156	0.878
-0.771	0.894					
Scaled_Sear	${ t chCountForDepression}$	0.0	706	0.086	0.817	0.426
-0.113	0.254					
CovidPercPo	sitive	-0.4	:031	0.351	-1.147	0.268
-1.148	0.342					
========			=======	======		=======
Omnibus:		0.621	Durbin-W	atson:		1.761
Prob(Omnibu	s):	0.733	Jarque-B	era (JB)	):	0.638
Skew:		-0.093	Prob(JB)	:		0.727
Kurtosis:		2.187	Cond. No			2.90e+17
========			=======	======		========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The smallest eigenvalue is 6.03e-34. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

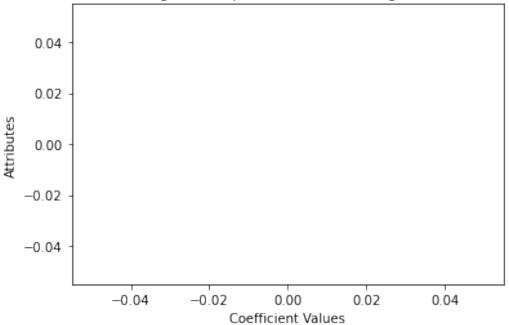
Plot for Linear Model Coefficients for Our Model:

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1807615713.py:1
9: 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 city\_combined\_dataset\_covid['CovidPercPositive'] = perc

# Attributes with significant p-values contributing towards crime rate



Regression for the same time frame without considering Covid Cases:

## Our Model:

Linear Model summary:

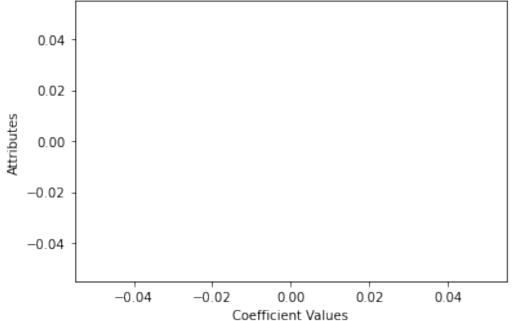
===========	==========	=====			=======
Dep. Variable:	Scaled_CrimeCount	R-sqı	uared:		0.195
Model:	OLS	Adj.	R-squared:		0.005
Method:	Least Squares	F-sta	atistic:		1.028
Date:	Sun, 11 Dec 2022	Prob	(F-statistic	c):	0.421
Time:	16:45:24	Log-I	Likelihood:		33.118
No. Observations:	22	AIC:			-56.24
Df Residuals:	17	BIC:			-50.78
Df Model:	4				
Covariance Type:	nonrobust				
	:				
		coef	std err	t	P> t
[0.025 0.975]					
	•				
Gender_ratio	-0.	0043	0.291	-0.015	0.988
-0.617 0.609					
Scaled_Unemployment	0	0309	0.067	0.462	0.650
Doaroa_onomproymone	0.	0000	0.007	0.102	0.000

-0.110	0.172					
Scaled_Media	anIncomeRate	0.2	549	0.194	1.314	0.206
-0.154	0.664					
WorkforceCou	int	0.0	012	0.011	0.112	0.912
-0.022	0.024					
PercentNegat	civeUsers	-0.3	802	0.636	-0.598	0.558
-1.721	0.961					
FavorOfDemoc	crats	0.0	800	0.393	0.002	0.998
-0.828	0.829					
Scaled_Searc	${\tt chCountForDepression}$	0.0	879	0.086	1.023	0.320
-0.093	0.269					
Omnibus:		2.374	Durbin	-Watson:		1.756
Prob(Omnibus	s):	0.305	Jarque	-Bera (JB)	:	1.193
Skew:		-0.151	Prob(J	B):		0.551
Kurtosis:		1.900	Cond.	No.		3.81e+17
=========			======	=======		========

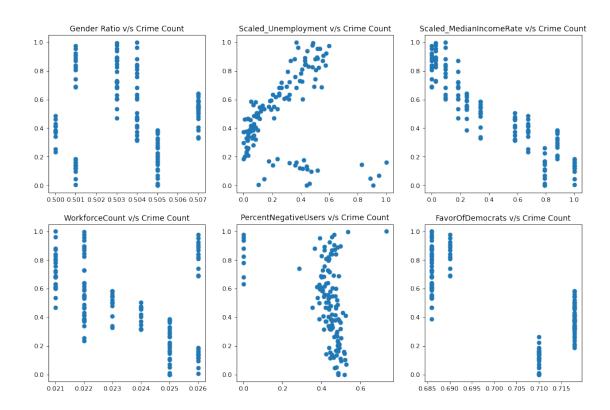
- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The smallest eigenvalue is 3.48e-34. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Plot for Linear Model Coefficients for Our Model:





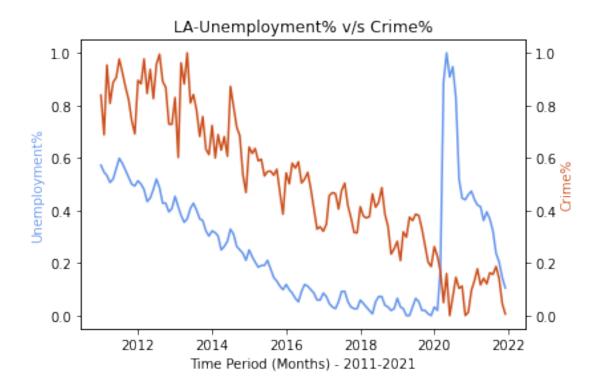
#### Correlation Graphs:



/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



## CHICAGO:

Before Covid (Mar-2020)

Ground Truth:

Linear Model summary:

=======================================				
Dep. Variable:	Scaled_CrimeCount	R-squared:		0.777
Model:	OLS	Adj. R-squared:		0.770
Method:	Least Squares	F-statistic:		122.8
Date:	Sun, 11 Dec 2022	<pre>Prob (F-statistic):</pre>		2.33e-34
Time:	16:45:25	Log-Likelihood:		105.41
No. Observations:	110	AIC:		-202.8
Df Residuals:	106	BIC:		-192.0
Df Model:	3			
Covariance Type:	nonrobust			
=======================================			=======	
========				
	coef	std err t	P> t	[0.025

## 0.975]

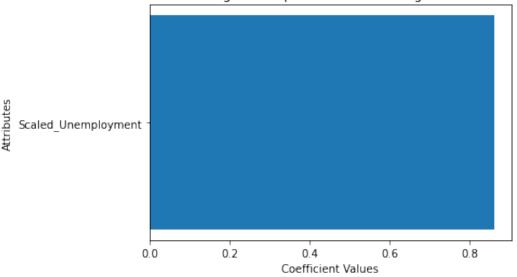
const	3.8112	3.316	1.149	0.253	-2.764
10.386					
Gender_ratio	-6.5741	6.382	-1.030	0.305	-19.227
6.079					
Scaled_Unemployment	0.8608	0.173	4.986	0.000	0.519
1.203					
${\tt Scaled\_MedianIncomeRate}$	-0.1702	0.108	-1.573	0.119	-0.385
0.044					
			========	========	
Omnibus:	5.500	Durbin-	Watson:		0.573
Prob(Omnibus):	0.064	Jarque-	Bera (JB):		3.443
Skew:	-0.252	Prob(JB	):		0.179
Kurtosis:	2.295	Cond. N	0.		960.

## Notes:

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

Plot for Linear Model Coefficients for Ground Truth:

Attributes with significant p-values contributing towards crime rate



## Our Model:

Linear Model summary:

## OLS Regression Results

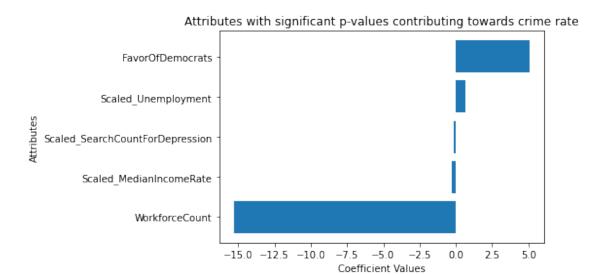
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Scaled_CrimeCount OLS Least Squares Sun, 11 Dec 2022 16:45:25 110 102 7 nonrobust	Adj. F-st Prob	======== uared: R-squared: atistic: (F-statisti Likelihood:	c):	0.805 0.791 60.05 2.37e-33 112.82 -209.6 -188.0
[0.025 0.975]		coef	std err	t	P> t
const -6.103 9.833		 8651	4.017	0.464	0.643
Gender_ratio -22.065 4.593 Scaled_Unemployment 0.274 0.977		7363 6259	6.720 0.177	-1.300 3.532	0.197
Scaled_MedianIncome -0.503 -0.020	Rate -0.	2615	0.122	-2.149	0.034
WorkforceCount -29.425 -1.173	-15.	2992	7.122	-2.148	0.034
PercentNegativeUser -0.094 0.330		1180	0.107	1.104	0.272
FavorOfDemocrats 0.667 9.513	5.	0899	2.230	2.283	0.025
Scaled_SearchCountF -0.216 -0.024	orDepression -0.	1202	0.049	-2.477	0.015
Omnibus: Prob(Omnibus): Skew: Kurtosis:	4.584 0.101 -0.205 2.320	Jarq Prob Cond	======== in-Watson: ue-Bera (JB) (JB): . No.		0.612 2.888 0.236 1.47e+03

## Notes:

Plot for Linear Model Coefficients for Our Model:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 1.47e+03. This might indicate that there are strong multicollinearity or other numerical problems.



Our Model without ground truth: Linear Model summary:

=======================================		======	========		========
Dep. Variable:	Scaled_CrimeCour	it R-s	quared:		0.235
Model:	OI	S Adj	. R-squared	:	0.211
Method:	Least Square	s F-s	statistic:		9.769
Date:	Sun, 11 Dec 202	2 Pro	b (F-statis	tic):	6.37e-07
Time:	16:45:2	.5 Log	-Likelihood	:	12.958
No. Observations:	13	_			-15.92
Df Residuals:	12	7 BIC	<b>:</b> :		-1.503
Df Model:		4			
Covariance Type:	nonrobus	t			
=======================================	=========	======		=======	=========
=======================================					
		coef	std err	t	P> t
[0.025 0.975]					
const	-1	1.6414	3.309	-3.518	0.001
-18.189 -5.094					
WorkforceCount	-1	8.9933	14.044	-1.352	0.179
-46.785 8.798					
PercentNegativeUser	S	0.3077	0.251	1.228	0.222
-0.188 0.803					
FavorOfDemocrats	1	7.4337	5.001	3.486	0.001
7.538 27.329					
Scaled_SearchCountF	orDepression -	0.3310	0.092	-3.608	0.000
	-				

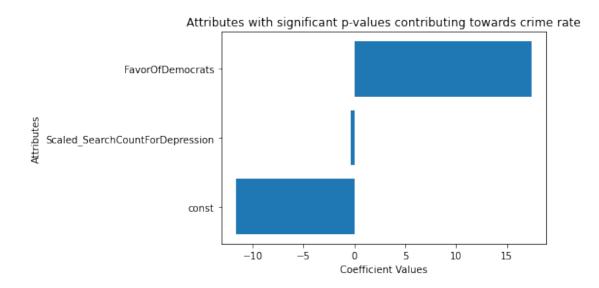
#### -0.513 -0.149

Omnibus:	5.838	Durbin-Watson:	0.144
Prob(Omnibus):	0.054	Jarque-Bera (JB):	6.010
Skew:	-0.510	Prob(JB):	0.0495
Kurtosis:	2.774	Cond. No.	1.05e+03

#### Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.05e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model without ground truth:



Till Dec-2021

#### Ground Truth:

Linear Model summary:

OLS Regression Results

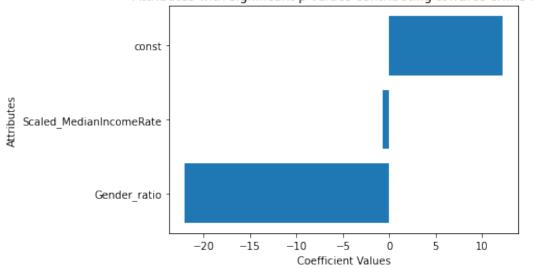
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.842
Model:	OLS	Adj. R-squared:	0.839
Method:	Least Squares	F-statistic:	227.8
Date:	Sun, 11 Dec 2022	<pre>Prob (F-statistic):</pre>	3.87e-51

Time: No. Observations: Df Residuals: Df Model: Covariance Type:	16:45:25 132 128 3 nonrobust	AIC:	relihood:		117.15 -226.3 -214.8
0.975]	coef	std err	t	P> t	[0.025
const	12.1945	3.184	3.830	0.000	5.894
18.495 Gender_ratio -9.788	-22.0308	6.187	-3.561	0.001	-34.273
Scaled_Unemployment 0.012	-0.1000	0.057	-1.766	0.080	-0.212
Scaled_MedianIncomeRate -0.704	-0.7663	0.032	-24.223	0.000	-0.829
Omnibus:	0.946	======= -Durbin	 -Watson:		0.554
Prob(Omnibus):	0.623	Jarque-	-Bera (JB):		0.959
Skew:	0.060	-			0.619
Kurtosis:	2.600	Cond. N	lo . 	.=======	980. =====

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

Plot for Linear Model Coefficients for Ground Truth:





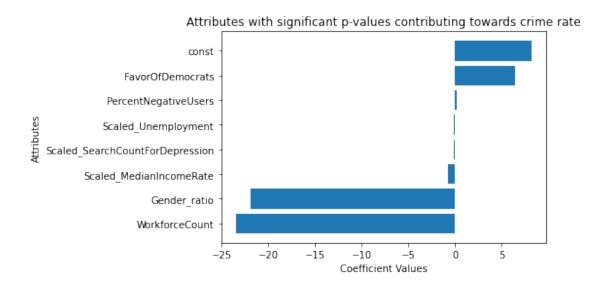
Our Model: Linear Model summary:

=======================================		======	=======		
Dep. Variable:	Scaled_CrimeCount	R-squa	red:		0.872
Model:	OLS	Adj. R	-squared:		0.865
Method:	Least Squares	F-stat	istic:		120.5
Date:	Sun, 11 Dec 2022	Prob (	F-statist:	ic):	3.33e-52
Time:	16:45:25	Log-Li	kelihood:		130.85
No. Observations:	132	AIC:			-245.7
Df Residuals:	124	BIC:			-222.6
Df Model:	7				
Covariance Type:	nonrobust				
	===========	======	=======	========	
		coef	std err	t	P> t
[0.025 0.975]					, ,
const	8.	2253	3.782	2.175	0.032
0.740 15.711					
Gender_ratio	-21.	8722	5.990	-3.652	0.000
-33.727 -10.017					
Scaled_Unemployment	-0.	1198	0.058	-2.053	0.042
-0.235 -0.004					
Scaled_MedianIncome	Rate -0.	7440	0.030	-24.400	0.000
-0.804 -0.684					
WorkforceCount	-23.	4736	5.852	-4.011	0.000

-35.056 -11.891						
PercentNegativeUsers	0.2	2090	0.105	1.988	0.049	
0.001 0.417						
FavorOfDemocrats	6.4	4892	2.224	2.918	0.004	
2.087 10.891						
Scaled_SearchCountForDepressi	on -0.1	1277	0.041	-3.150	0.002	
-0.208 -0.047						
		======				
Omnibus:	0.423	Durbin	-Watson:		0.626	
<pre>Prob(Omnibus):</pre>	0.809	Jarque	-Bera (JB)	:	0.572	
Skew:	-0.017	Prob(J	B):		0.751	
Kurtosis:	2.679	Cond.	No.		1.39e+03	
	:=======	======	=======	========	========	

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.39e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

OLS Regression Results

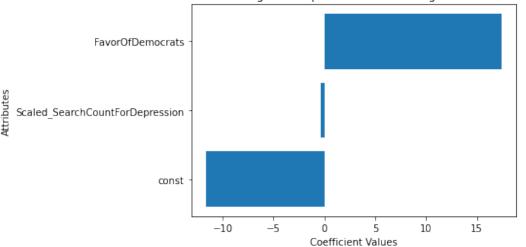
Dep. Variable: Scaled\_CrimeCount R-squared: 0.235
Model: 0LS Adj. R-squared: 0.211

Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	nonrobi	022 :25 132 127 4	Prob Log-I AIC: BIC:	(F-statisti Likelihood:		9.769 6.37e-07 12.958 -15.92 -1.503
[0.025 0.975]			coef	std err	t	P> t
const	-	-11.6	5414	3.309	-3.518	0.001
-18.189 -5.094						
WorkforceCount	-	-18.9	9933	14.044	-1.352	0.179
-46.785 8.798						
PercentNegativeUsers		0.3	3077	0.251	1.228	0.222
-0.188 0.803						
FavorOfDemocrats		17.4	1337	5.001	3.486	0.001
7.538 27.329						
Scaled_SearchCountFo	rDepression	-0.3	3310	0.092	-3.608	0.000
-0.513 -0.149						
Omnibus:	 5 2	==== 338	Durb	======= in-Watson:	:=======	0.144
Prob(Omnibus):		)54		in watson. ie-Bera (JB)	•	6.010
Skew:			Prob		•	0.0495
Kurtosis:		774	Cond			1.05e+03
=======================================		====				========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.05e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model without ground truth:





## Covid Data Comparison:

Regression from Mar-2020 to Dec-2021 along with Covid Positive Cases Per Month:

## Our Model:

Linear Model summary:

Dep. Variable:	${\tt Scaled\_CrimeCount}$	R-sqı	uared:		0.491
Model:	OLS	Adj.	R-squared:		0.331
Method:	Least Squares	F-sta	atistic:		3.082
Date:	Sun, 11 Dec 2022	Prob	(F-statistic	c):	0.0389
Time:	16:45:25	Log-I	Likelihood:		41.161
No. Observations:	22	AIC:			-70.32
Df Residuals:	16	BIC:			-63.78
Df Model:	5				
Covariance Type:	nonrobust				
=======================================					========
	:				
		coef	std err	t	P> t
[0.025 0.975]					
Gender_ratio	0.	3230	0.120	2.689	0.016
0.068 0.578					
Scaled_Unemployment	-0.	1164	0.059	-1.961	0.067
-0.242 0.009					
Scaled_MedianIncome	Rate -0.	4951	0.139	-3.574	0.003

-0.789	-0.201					
WorkforceC	ount	0.0	155	0.007	2.280	0.037
0.001	0.030					
PercentNeg	ativeUsers	0.1	.907	0.326	0.585	0.567
-0.501	0.882					
FavorOfDem	ocrats	0.4	1663	0.173	2.689	0.016
0.099	0.834					
Scaled_Sea	${\tt rchCountForDepression}$	0.1	.280	0.086	1.488	0.156
-0.054	0.310					
CovidPercP	ositive	-0.4	1447	0.238	-1.870	0.080
-0.949	0.059					
=======	=======================================	======				
Omnibus:		3.575	Durbi	n-Watson:		2.116
Prob(Omnib	us):	0.167	Jarqu	e-Bera (JB)	:	1.457
Skew:		0.182	Prob(	JB):		0.483
Kurtosis:		1.793	Cond.	No.		3.38e+18
========	============	======	======	========	=======	========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The smallest eigenvalue is 4.04e-36. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

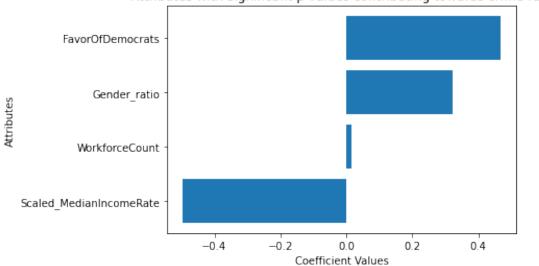
Plot for Linear Model Coefficients for Our Model:

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1807615713.py:1
9: 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 city\_combined\_dataset\_covid['CovidPercPositive'] = perc





Regression for the same time frame without considering Covid Cases:

## Our Model:

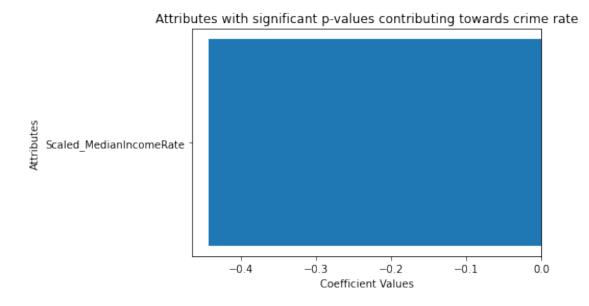
Linear Model summary:

		=====	========	.=======		
Dep. Variable:	Scaled_CrimeCount	ed_CrimeCount R-squared:				
Model:	OLS	-	R-squared:		0.233	
Method:	Least Squares	F-st	atistic:		2.596	
Date:	Sun, 11 Dec 2022	Prob	(F-statisti	lc):	0.0734	
Time:	16:45:25	Log-	Likelihood:		38.986	
No. Observations:	22	AIC:			-67.97	
Df Residuals:	17	BIC:			-62.52	
Df Model:	4					
Covariance Type:	nonrobust					
=======================================	=======================================	=====		.======		
	:					
		coef	std err	t	P> t	
[0.025 0.975]						
Gender_ratio	0.	2576	0.123	2.093	0.052	
-0.002 0.517						
Scaled_Unemployment	-0.	1220	0.063	-1.922	0.072	
-0.256 0.012						
Scaled_MedianIncome	Rate -0.	4436	0.145	-3.051	0.007	
-0.750 -0.137						

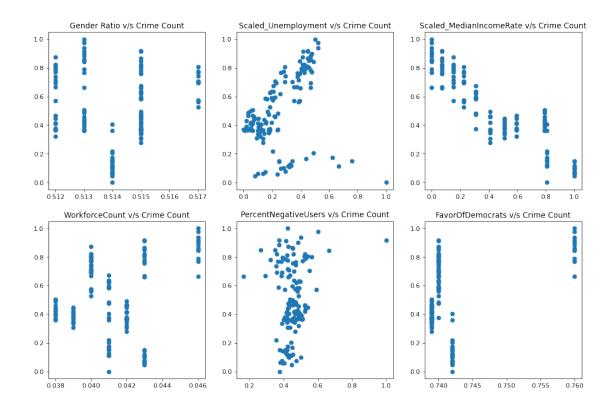
WorkforceCou	int	0.0	119	0.007	1.701	0.107
-0.003	0.027					
PercentNegat	iveUsers	0.3	3433	0.338	1.015	0.324
-0.370	1.057					
FavorOfDemoc	crats	0.3	3719	0.178	2.093	0.052
-0.003	0.747					
Scaled_Searc	${\tt chCountForDepression}$	0.0	235	0.070	0.336	0.741
-0.124	0.171					
Omnibus:	=======================================	1.146	Dumbin	======= -Watson:		1.791
J	-					
Prob(Omnibus	s):	0.564	Jarque-	·Bera (JB)	:	0.834
Skew:		-0.092	Prob(JE	3):		0.659
Kurtosis:		2.064	Cond. N	lo.		5.82e+18
=========		======	======	=======		========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The smallest eigenvalue is 1.36e-36. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Plot for Linear Model Coefficients for Our Model:



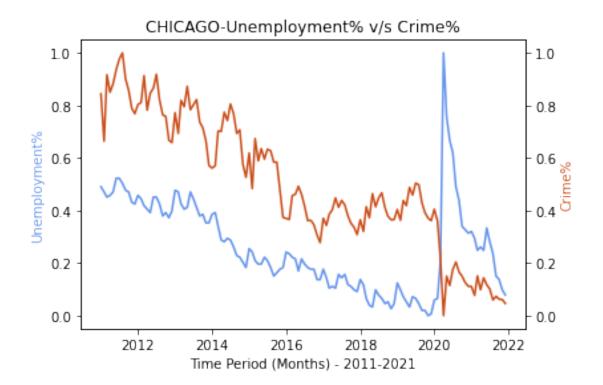
## Correlation Graphs:



/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



## NASHVILLE:

Before Covid (Mar-2020)

Ground Truth:

Linear Model summary:

## OLS Regression Results

=======================================			=========
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.058
Model:	OLS	Adj. R-squared:	0.009
Method:	Least Squares	F-statistic:	1.190
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	0.322
Time:	16:45:26	Log-Likelihood:	16.556
No. Observations:	62	AIC:	-25.11
Df Residuals:	58	BIC:	-16.60
Df Model:	3		
Covariance Type:	nonrobust		
=======================================			
========			

 $\texttt{coef} \qquad \texttt{std err} \qquad \qquad \texttt{t} \qquad \texttt{P>|t|} \qquad \texttt{[0.025]}$ 

#### 0.975]

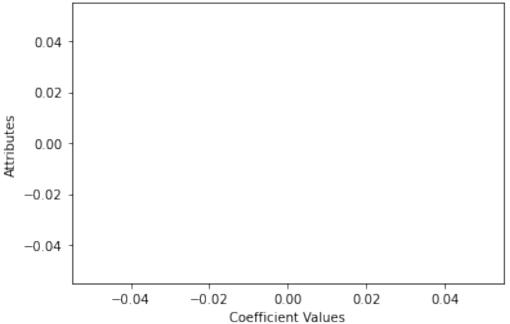
const	25.2928	21.064	1.201	0.235	-16.871
67.456					
Gender_ratio	-47.2977	40.717	-1.162	0.250	-128.802
34.207	-0.2374	1 015	-0.234	0.816	-2.269
Scaled_Unemployment 1.795	-0.2374	1.015	-0.234	0.010	-2.209
Scaled_MedianIncomeRate	-0.2129	0.152	-1.404	0.166	-0.516
0.091					
				=======	=======
Omnibus:	13.969	Durbin-	Watson:		1.196
Prob(Omnibus):	0.001	Jarque-	Bera (JB):		16.279
Skew:	-0.966	Prob(JB	3):		0.000292
Kurtosis:	4.604	Cond. N	lo.		2.31e+03
=======================================		=======	========	=======	=======

#### Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.31e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Ground Truth:

# Attributes with significant p-values contributing towards crime rate



Our Model:

Linear Model summary:

# OLS Regression Results

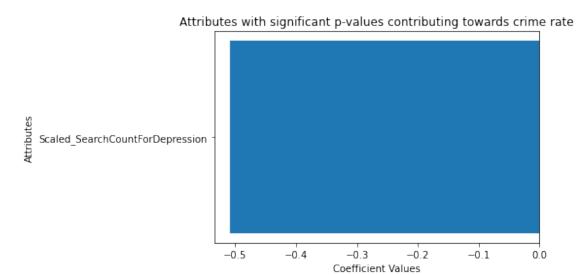
	==============				========	
Dep. Variable:	Scaled_CrimeCount	l_CrimeCount R-squared:				
Model:	OLS	OLS Adj. R-squared:				
Method:	Least Squares	F-s	tatistic:		4.081	
Date:	Sun, 11 Dec 2022	Prol	b (F-statisti	.c):	0.00117	
Time:	16:45:26	Log-	-Likelihood:		27.867	
No. Observations:	62	AIC	:		-39.73	
Df Residuals:	54	BIC	:		-22.72	
Df Model:	7					
Covariance Type:	nonrobust					
=======================================	===========	=====		:======		
=======================================		_	_			
[0 005 0 075]		coef	std err	t	P> t	
[0.025 0.975]						
const	29.	6462	25.376	1.168	0.248	
-21.229 80.521						
Gender_ratio	-51.	5976	49.685	-1.038	0.304	
-151.210 48.01	5					
Scaled_Unemployment	-1.	1478	0.913	-1.257	0.214	
-2.978 0.683						
Scaled_MedianIncome	Rate -0.	1912	0.135	-1.414	0.163	
-0.462 0.080						
WorkforceCount		1483	9.365	0.657	0.514	
-12.627 24.923						
PercentNegativeUser	o.	0516	0.611	0.084	0.933	
-1.174 1.277						
FavorOfDemocrats	-3.	4526	2.498	-1.382	0.173	
-8.460 1.555						
Scaled_SearchCountF	orDepression -0.	5094	0.107	-4.753	0.000	
-0.724 -0.294						
Omnibus:	8.402		======== bin-Watson:	.=======	1.828	
Prob(Omnibus):	0.015		que-Bera (JB)	•	7.749	
Skew:	-0.760		-	•	0.0208	
Kurtosis:	3.828		d. No.		3.97e+03	
Mul 00515.			u. NO. ========		3.976.03	

## Notes:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 3.97e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth:

Linear Model summary:

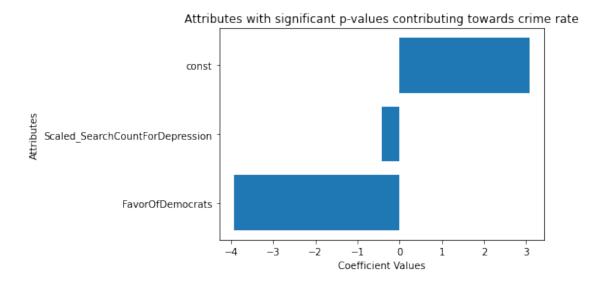
OLS Regression Results

Dep. Variable:	Scaled_CrimeCount	R-sqı	uared:		0.285
Model:	OLS	Adj.	R-squared:		0.249
Method:	Least Squares	F-sta	atistic:		7.863
Date:	Sun, 11 Dec 2022	Prob	(F-statistic	:):	2.18e-05
Time:	16:45:26	Log-I	Likelihood:		25.564
No. Observations:	84	AIC:			-41.13
Df Residuals:	79	BIC:			-28.97
Df Model:	4				
Covariance Type:	nonrobust				
=======================================		======			=========
=======================================	=				
		coef	std err	t	P> t
[0.025 0.975]					
	_				
const	3.	0887	0.679	4.550	0.000
1.737 4.440					
WorkforceCount	-2.	9960	6.354	-0.472	0.639
-15.643 9.65	1				

PercentNegativeUsers	0.8	3915 0.5	1.591	0.116
-0.224 2.007				
FavorOfDemocrats	-3.9	9353 0.9	920 -4.279	0.000
-5.766 -2.105				
${\tt Scaled\_SearchCountForDepressi}$	on -0.4	1172 0.1	-4.188	0.000
-0.615 -0.219				
	=======			
Omnibus:	5.727	Durbin-Wats	son:	1.328
<pre>Prob(Omnibus):</pre>	0.057	Jarque-Bera	a (JB):	4.994
Skew:	-0.551	Prob(JB):		0.0823
Kurtosis:	3.462	Cond. No.		412.

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

Plot for Linear Model Coefficients for Our Model without ground truth:



Till Dec-2021

Ground Truth:

Linear Model summary:

OLS Regression Results

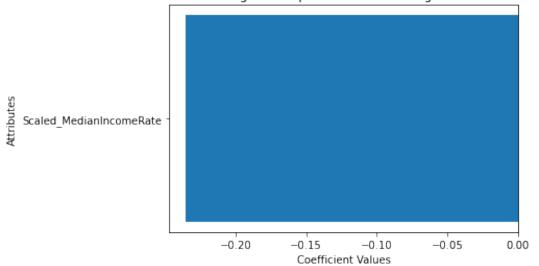
Dep. Variable: Scaled\_CrimeCount R-squared: 0.129

Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	OLS Least Squares Sun, 11 Dec 2022 16:45:26 84 80 3 nonrobust	F-stat Prob (	-squared: istic: F-statistic): kelihood:		0.097 3.963 0.0109 17.307 -26.61 -16.89
0.975]	coef	std err	t	P> t	[0.025
const 67.110 Gender_ratio	30.5696 -57.4840	18.361 35.408	1.665 -1.623	0.100	-5.971 -127.948
12.980 Scaled_Unemployment 0.131	-0.1250 ate -0.2351	0.128	-0.973 -3.025	0.333	-0.381 -0.390
Scaled_MedianIncomeRa -0.080			-3.025	0.003	-0.390
Omnibus:	10.873		-Watson:		1.043
Prob(Omnibus):	0.004	-	-Bera (JB):		11.215
Skew: Kurtosis:	-0.756 3.958	Prob(J) Cond.	No.		0.00367 2.32e+03 ======

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.32e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Ground Truth:





## Our Model:

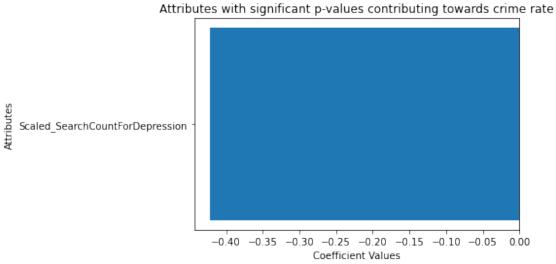
Linear Model summary:

=======================================				
Dep. Variable:	Scaled_CrimeCount	R-squared:		0.319
Model:	OLS	Adj. R-squared:		0.257
Method:	Least Squares	F-statistic:		5.097
Date:	Sun, 11 Dec 2022	Prob (F-statist	ic):	8.82e-05
Time:	16:45:26	Log-Likelihood:		27.655
No. Observations:	84	AIC:		-39.31
Df Residuals:	76	BIC:		-19.86
Df Model:	7			
Covariance Type:	nonrobust			
=======================================				
		coef std err	t	P> t
[0.025 0.975]				
const	17	7534 24.250	1.969	0.053
-0.544 96.051	<b>T1.</b>	7554 24.250	1.909	0.033
Gender_ratio	-88.	9294 47.761	-1.862	0.066
-184.053 6.19				
Scaled_Unemployment	-0.	0661 0.143	-0.461	0.646
-0.352 0.219				
Scaled_MedianIncome	Rate -0.	1551 0.112	-1.390	0.169
-0.378 0.067				
WorkforceCount	8.	6963 9.930	0.876	0.384

-11.081	28.473					
PercentNega	tiveUsers	0.8	3941	0.568	1.574	0.120
-0.237	2.025					
FavorOfDemo	crats	-2.1	1912	1.689	-1.297	0.198
-5.555	1.173					
Scaled_Sear	chCountForDepression	on -0.4	1226	0.102	-4.150	0.000
-0.625	-0.220					
		2 042				4 265
Omnibus:		3.943		n-Watson:		1.365
Prob(Omnibu	ເຮ):	0.139	Jarqu	e-Bera (JB)	:	3.213
Skew:		-0.446	Prob(	JB):		0.201
Kurtosis:		3.351	Cond.	No.		4.13e+03
========	:==========			========	========	========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.13e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth:

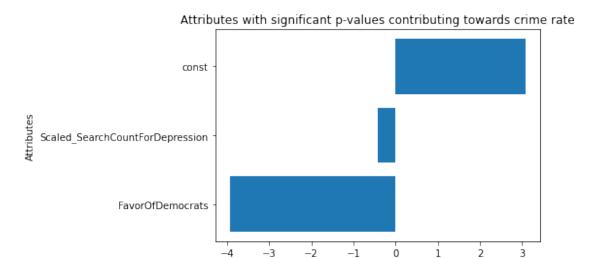
Linear Model summary:

Dep. Variable:	Scaled_CrimeCount	R-squared:	0.285
Model:	OLS	Adj. R-squared:	0.249

Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Least Squares Sun, 11 Dec 2022 16:45:26 84 79 4 nonrobust	Prob Log- AIC: BIC:	(F-statisti Likelihood:		7.863 2.18e-05 25.564 -41.13 -28.97
=======================================					
[0.025 0.975]		coef	std err	t 	P> t
const	3.	.0887	0.679	4.550	0.000
1.737 4.440					
WorkforceCount	-2.	.9960	6.354	-0.472	0.639
-15.643 9.651					
PercentNegativeUsers	0.	.8915	0.560	1.591	0.116
-0.224 2.007					
FavorOfDemocrats	-3.	. 9353	0.920	-4.279	0.000
-5.766 -2.105		4.450		4 400	
Scaled_SearchCountFo	rDepression -0.	.4172	0.100	-4.188	0.000
-0.615 -0.219					
Omnibus:	5.727	Durb	in-Watson:		1.328
Prob(Omnibus):	0.057		ue-Bera (JB)	:	4.994
Skew:	-0.551	-			0.0823
Kurtosis:	3.462		. No.		412.
	=======================================				=======

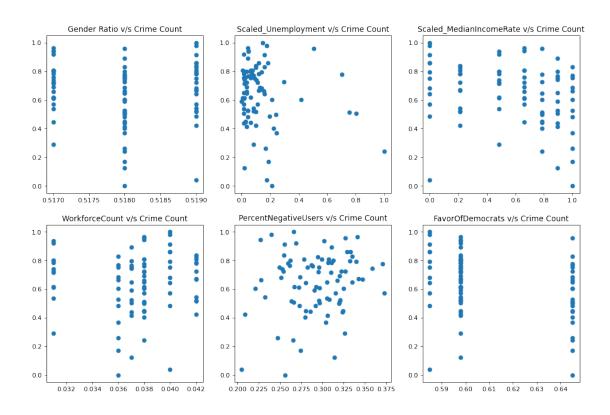
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Plot for Linear Model Coefficients for Our Model without ground truth:



Coefficient Values

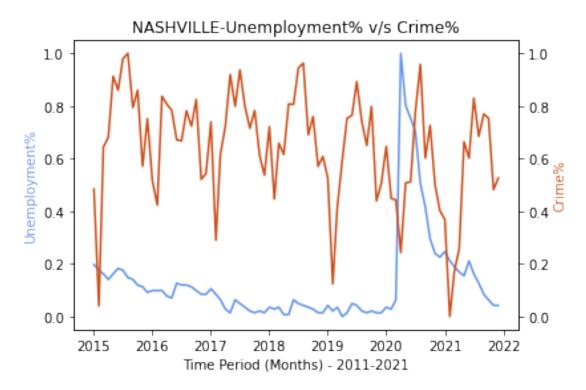
## Correlation Graphs:



the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



**BOSTON:** 

Before Covid (Mar-2020)

Ground Truth:

Linear Model summary:

OLS Regression Results

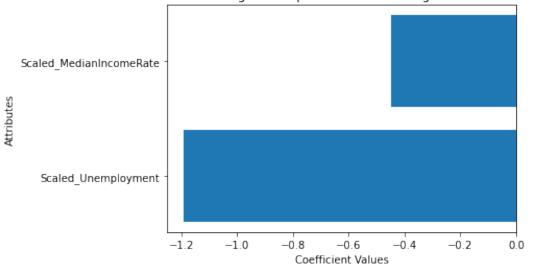
Dep. Variable: Scaled\_CrimeCount R-squared: 0.155
Model: OLS Adj. R-squared: 0.126

Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:		16:45:27 92 88	2 Prob (7 Log-Li 2 AIC: 3 BIC:	istic: (F-statistic): kelihood:		5.365 0.00194 36.943 -65.89 -55.80
0.975]		coef	std err	t	P> t	[0.025
const		6.7389	5.868	1.148	0.254	-4.922
18.400						
Gender_ratio		-11.0116	11.369	-0.969	0.335	-33.605
11.582		_1 1019	0.396	-3.007	0.003	-1.979
Scaled_Unemployment -0.404		-1.1918	0.396	-3.007	0.003	-1.979
Scaled_MedianIncomeRa	ate	-0.4468	0.147	-3.037	0.003	-0.739
-0.154						
Omnibus:		======================================		======== n-Watson:	:======:	1.020
Prob(Omnibus):		0.000		e-Bera (JB):		55.350
Skew:		-1.09	-			9.57e-13
Kurtosis:		6.10	5 Cond.	No.		877.

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

Plot for Linear Model Coefficients for Ground Truth:





# Our Model:

Linear Model summary:

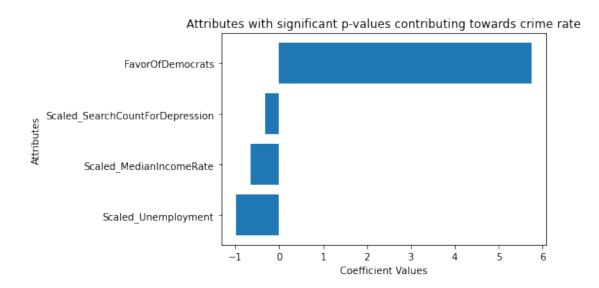
OLS Regression Results

=======================================		======		=======	=======
Dep. Variable:	Scaled_CrimeCount	R-sqı	uared:		0.456
Model:	OLS	Adj.	R-squared:		0.411
Method:	Least Squares	F-sta	atistic:		10.07
Date:	Sun, 11 Dec 2022	Prob	(F-statisti	c):	4.42e-09
Time:	16:45:27	Log-I	Likelihood:		57.244
No. Observations:	92	AIC:			-98.49
Df Residuals:	84	BIC:			-78.31
Df Model:	7				
Covariance Type:	nonrobust				
	============	=====	========	=======	
		coef	std err	t	P> t
[0.025 0.975]		COGI	Sta ell	U	17   0
	_				
const	3.	6810	5.353	0.688	0.494
-6.965 14.327					
Gender_ratio		7624	9.638	-1.324	0.189
-31.929 6.404					
Scaled_Unemployment	-0.	9871	0.370	-2.670	0.009
-1.722 -0.252					
Scaled_MedianIncome	Rate -0.	6493	0.136	-4.763	0.000
-0.920 -0.378					
WorkforceCount	-7.	3452	5.313	-1.383	0.170

-17.910	3.219					
PercentNegati	veUsers	-0.4	1246	0.251	-1.694	0.094
-0.923	0.074					
FavorOfDemocr	ats	5.7	494	1.455	3.951	0.000
2.856	3.643					
Scaled_Search	CountForDepression	n -0.3	3163	0.071	-4.437	0.000
-0.458 -	0.175					
	=========	======			========	
Omnibus:		62.383	Durbin-	Watson:		1.804
Prob(Omnibus)	:	0.000	Jarque-	Bera (JB	):	369.691
Skew:		-2.081	Prob(JE	3):		5.28e-81
Kurtosis:		11.895	Cond. N	lo.		1.22e+03
		=======	======	======	========	

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.22e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

J

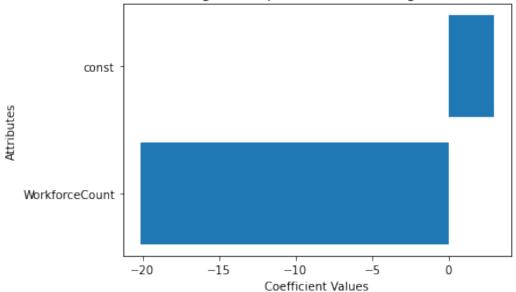
=======================================			======
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.147
Model:	OLS	Adj. R-squared:	0.116

Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	114 109 4 nonrobust	Prob		.c):	4.704 0.00153 20.606 -31.21 -17.53
[0.025 0.975]		coef	std err	t 	P> t
const	2.	9348	0.776	3.780	0.000
1.396 4.473					
WorkforceCount	-20.	1339	6.048	-3.329	0.001
-32.121 -8.147					
PercentNegativeUsers	-0.	5454	0.363	-1.501	0.136
-1.265 0.175					
FavorOfDemocrats	-1.	5521	0.945	-1.642	0.103
-3.425 0.321					
Scaled_SearchCountFo	orDepression -0.	1523	0.087	-1.753	0.082
-0.324 0.020					
Omnibus:			n-Watson:		0.626
Prob(Omnibus):	0.001		e-Bera (JB)	):	14.911
Skew:	-0.790	-			0.000578
Kurtosis:	3.803	Cond.	No.		445.
		======	========		========

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

Plot for Linear Model Coefficients for Our Model without ground truth:

# Attributes with significant p-values contributing towards crime rate



## Till Dec-2021

Ground Truth:

Linear Model summary:

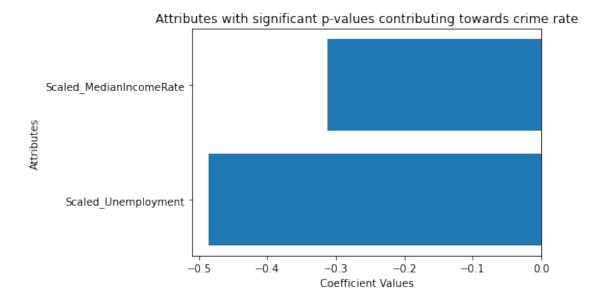
#### OLS Regression Results

ULS Regression Results						
Dep. Variable: Model: Method:	Scaled_CrimeCount  OLS  Least Squares	R-squared: Adj. R-squared: F-statistic:		0.406 0.389 25.02		
Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Sun, 11 Dec 2022	Prob (F-statistic): Log-Likelihood: AIC: BIC:		2.05e-12 41.175 -74.35 -63.41		
0.975]	coef	std err t	P> t	[0.025		
const 13.410 Gender_ratio 15.747	3.0473 -4.2061	5.229 0.583 10.068 -0.418	0.561	-7.315 -24.159		

${\tt Scaled\_Unemployment}$	-0.4855	0.095	-5.132	0.000	-0.673
-0.298					
Scaled_MedianIncomeRate	-0.3119	0.053	-5.913	0.000	-0.416
-0.207					
Out the second	16.010	Dl-i 17-			0.004
Omnibus:	16.919	Durbin-Wa	itson:		0.804
<pre>Prob(Omnibus):</pre>	0.000	Jarque-Be	era (JB):		22.552
Skew:	-0.773	Prob(JB):			1.27e-05
Kurtosis:	4.534	Cond. No.			865.
					=======

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

Plot for Linear Model Coefficients for Ground Truth:



## Our Model: Linear Model summary:

## OLS Regression Results

Dep. Variable:	Scaled_CrimeCount	R-squared:	0.600
Model:	OLS	Adj. R-squared:	0.573
Method:	Least Squares	F-statistic:	22.70
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	1.58e-18
Time:	16:45:27	Log-Likelihood:	63.738
No. Observations:	114	AIC:	-111.5

coef std err t P> t   [0.025	Df Residuals: Df Model: Covariance Type: non	106 BIC: 7			-89.59
[0.025					
[0.025		coef	std err	t	P> t.
-9.200 12.050  Gender_ratio -8.1040 9.358 -0.866 0.388 -26.656 10.448  Scaled_Unemployment -0.3978 0.092 -4.335 0.000 -0.580 -0.216	[0.025 0.975]				
-9.200 12.050  Gender_ratio -8.1040 9.358 -0.866 0.388 -26.656 10.448  Scaled_Unemployment -0.3978 0.092 -4.335 0.000 -0.580 -0.216					
Gender_ratio -8.1040 9.358 -0.866 0.388 -26.656 10.448  Scaled_Unemployment -0.3978 0.092 -4.335 0.000 -0.580 -0.216	const	1.4250	5.359	0.266	0.791
-26.656 10.448 Scaled_Unemployment -0.3978 0.092 -4.335 0.000 -0.580 -0.216	-9.200 12.050				
Scaled_Unemployment -0.3978 0.092 -4.335 0.000 -0.580 -0.216	Gender_ratio	-8.1040	9.358	-0.866	0.388
-0.580 -0.216	-26.656 10.448				
		-0.3978	0.092	-4.335	0.000
	-0.580 -0.216				
=	Scaled_MedianIncomeRate	-0.6313	0.100	-6.305	0.000
-0.830 -0.433	-0.830 -0.433				
WorkforceCount -19.3595 4.582 -4.225 0.000	WorkforceCount	-19.3595	4.582	-4.225	0.000
-28.443 -10.276					
PercentNegativeUsers -0.3063 0.256 -1.197 0.234	PercentNegativeUsers	-0.3063	0.256	-1.197	0.234
-0.813 0.201	-0.813 0.201				
FavorOfDemocrats 5.9098 1.381 4.278 0.000	FavorOfDemocrats	5.9098	1.381	4.278	0.000
3.171 8.649	3.171 8.649				
Scaled_SearchCountForDepression -0.2234 0.063 -3.547 0.001	<del>-</del>	-0.2234	0.063	-3.547	0.001
-0.348 -0.099					
Omnibus: 43.500 Durbin-Watson: 1.314					
Prob(Omnibus): 0.000 Jarque-Bera (JB): 133.275					
Skew: -1.356 Prob(JB): 1.15e-29		1		•	

Kurtosis:

7.550 Cond. No.

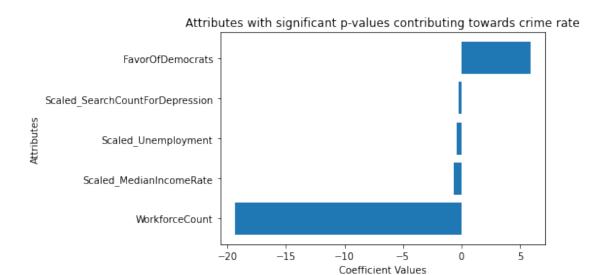
\_\_\_\_\_\_

1.29e+03

Plot for Linear Model Coefficients for Our Model:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 1.29e+03. This might indicate that there are strong multicollinearity or other numerical problems.



Our Model without ground truth: Linear Model summary:

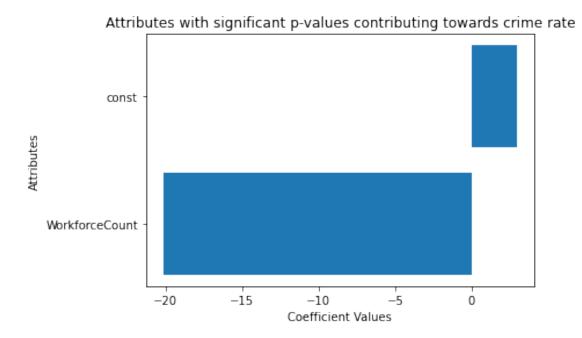
## OLS Regression Results

===========						
Dep. Variable: Model:	Scaled_CrimeC	ount OLS	-	uared: R-squared:		0.147 0.116
Method:	Least Squ	ares	_	_		4.704
Date:	Sun, 11 Dec				c):	0.00153
Time:				Likelihood:	•	20.606
No. Observations:			AIC:			-31.21
Df Residuals:		109	BIC:			-17.53
Df Model:		4				
Covariance Type:	nonro	bust				
=======================================		=====	=====		=======	
=======================================	==		coof	std err	t	P> t
[0.025 0.975]	]	(	coei	sta ell	· ·	F>
		0 (	20.40	0.774	0.700	0.000
const		2.9	9348	0.776	3.780	0.000
1.396 4.473		00	4000	0.040	0.000	0.004
WorkforceCount	4.77	-20.1	1339	6.048	-3.329	0.001
-32.121 -8.14		0 5	- 4 - 4	0.000	4 504	0.400
PercentNegativeUs		-0.8	5454	0.363	-1.501	0.136
-1.265 0.175	0	4 -		0.045	1 (10	0.400
FavorOfDemocrats	1	-1.8	5521	0.945	-1.642	0.103
-3.425 0.32		0 4	1500	0.007	1 750	0.000
Scaled_SearchCoun	-	-0.1	1523	0.087	-1.753	0.082
-0.324 0.020	J					

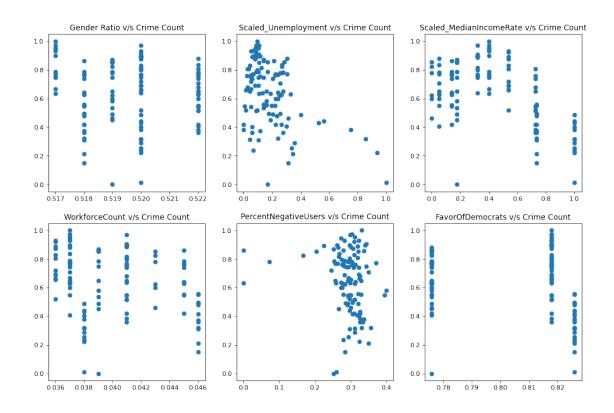
Omnibus:	13.750	Durbin-Watson:	0.626			
<pre>Prob(Omnibus):</pre>	0.001	Jarque-Bera (JB):	14.911			
Skew:	-0.790	Prob(JB):	0.000578			
Kurtosis:	3.803	Cond. No.	445.			

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

Plot for Linear Model Coefficients for Our Model without ground truth:



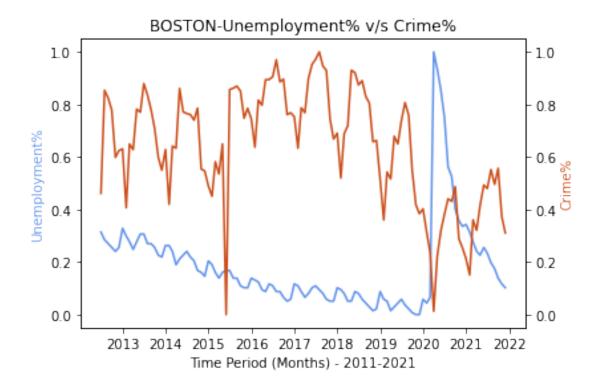
## Correlation Graphs:



/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



## SEATTLE:

Before Covid (Mar-2020)

Ground Truth:

Linear Model summary:

## OLS Regression Results

=======================================	=======================================		==========
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.179
Model:	OLS	Adj. R-squared:	0.156
Method:	Least Squares	F-statistic:	7.701
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	0.000105
Time:	16:45:28	Log-Likelihood:	186.98
No. Observations:	110	AIC:	-366.0
Df Residuals:	106	BIC:	-355.2
Df Model:	3		
Covariance Type:	nonrobust		
=======================================	=======================================		

coef std err t P>|t| [0.025]

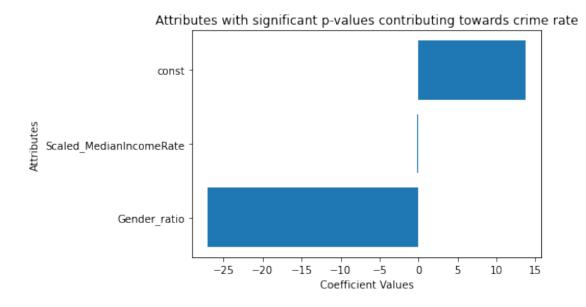
#### 0.975]

const	13.7158	3.497	3.923	0.000	6.783
20.648					
Gender_ratio	-27.0115	6.995	-3.862	0.000	-40.879
-13.144					
Scaled_Unemployment	-0.0643	0.065	-0.993	0.323	-0.193
0.064	0 1055	0 044	4 500	0.000	0.007
Scaled_MedianIncomeRate	-0.1855	0.041	-4.526	0.000	-0.267
-0.104					
Omnibus:	 15.992	 -Durbin	Watson:		1.581
Prob(Omnibus):	0.000		Bera (JB):		20.839
Skew:	-0.761	Prob(JB			2.98e-05
Kurtosis:	4.494	Cond. N	0.		2.14e+03
=======================================					=======

#### Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.14e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Ground Truth:



#### Our Model:

## Linear Model summary:

## OLS Regression Results

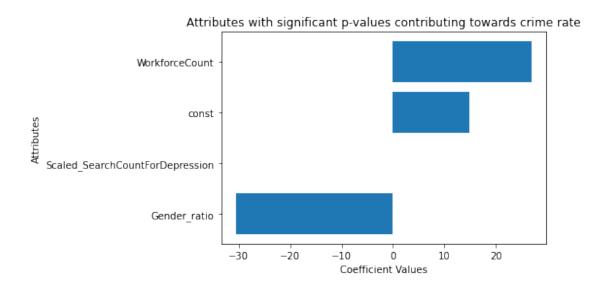
		=====			
Dep. Variable:	Scaled_CrimeCount	R-sc	quared:		0.269
Model:	OLS	Adj.	. R-squared:		0.219
Method:	Least Squares	F-st	tatistic:		5.368
Date:	Sun, 11 Dec 2022	Prob	o (F-statisti	c):	2.95e-05
Time:	16:45:28	Log-	-Likelihood:		193.39
No. Observations:	110	AIC:	:		-370.8
Df Residuals:	102	BIC	:		-349.2
Df Model:	7				
Covariance Type:	nonrobust				
=======================================	===========				=========
		coef	std err	t	P> t
[0.025 0.975]					
const	14.	7662	3.506	4.212	0.000
7.812 21.720	•		2 227	4 400	0.000
Gender_ratio		5726	6.887	-4.439	0.000
-44.232 -16.913		0000	0.070	0 075	0.700
Scaled_Unemployment	-0.	0263	0.070	-0.375	0.709
-0.165 0.113	D-+-	0100	0.000	0.000	0.025
Scaled_MedianIncome	Kate U.	0180	0.086	0.209	0.835
-0.153 0.189 WorkforceCount	06	0010	10 002	2.471	0.015
5.326 48.657	20.	9918	10.923	2.4/1	0.015
PercentNegativeUser	σ 0	0696	0.131	0.532	0.596
-0.190 0.329	δ 0.	0090	0.131	0.552	0.590
FavorOfDemocrats	-0	3303	0.580	-0.569	0.571
-1.482 0.821	0.	5505	0.000	0.005	0.071
Scaled_SearchCountF	orDenression -0	0544	0.022	-2.430	0.017
-0.099 -0.010	ordepression o.	0011	0.022	2.100	0.017
=======================================				=======	========
Omnibus:	27.653	Durk	oin-Watson:		1.926
Prob(Omnibus):	0.000	Jaro	que-Bera (JB)	:	48.804
Skew:	-1.077	Prob			2.53e-11
Kurtosis:	5.451		d. No.		3.93e+03
=======================================					

#### Notes:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 3.93e+03. This might indicate that there are strong multicollinearity or other numerical problems.

## Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

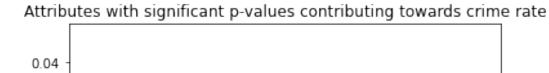
OLS Regression Results

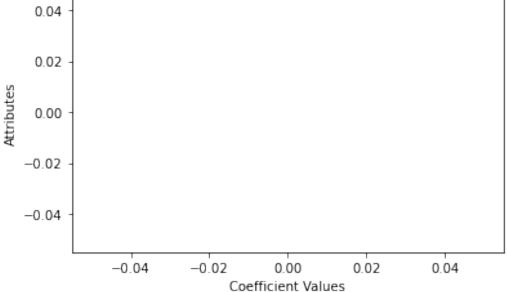
=======================================	:=========	=======================================		
Dep. Variable:	Scaled_CrimeCount	R-squared:		0.008
Model:	OLS	Adj. R-squared:		-0.024
Method:	Least Squares	F-statistic:		0.2467
Date:	Sun, 11 Dec 2022	Prob (F-statistic)	):	0.911
Time:	16:45:28	Log-Likelihood:		133.24
No. Observations:	132	AIC:		-256.5
Df Residuals:	127	BIC:		-242.1
Df Model:	4			
Covariance Type:	nonrobust			
=======================================	:=========	=======================================	-======	
=======================================				P. I. I
[0 005 0 075]		coef std err	t	P> t
[0.025 0.975]				
	_			
const	-0	1487 0.592	-0.251	0.802
-1.319 1.022	0.	1107 0.032	0.201	0.002
WorkforceCount	1.	2868 5.360	0.240	0.811
-9.320 11.894			0.210	0.022
PercentNegativeUser	rs -0.	1390 0.231	-0.602	0.548
-0.596 0.318				
FavorOfDemocrats	0.	4476 0.625	0.716	0.475
-0.789 1.684				

Scaled_Search -0.062	hCountForDepressi 0.092	on 0.0	0.039	0.380	0.704
		400 546		=======	4 060
Omnibus:		193.546	Durbin-Watson:		1.969
Prob(Omnibus)	):	0.000	Jarque-Bera (JB):		14902.790
Skew:		5.667	<pre>Prob(JB):</pre>		0.00
Kurtosis:		53.805	Cond. No.		935.

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

Plot for Linear Model Coefficients for Our Model without ground truth:





Till Dec-2021

Ground Truth:

Linear Model summary:

OLS Regression Results

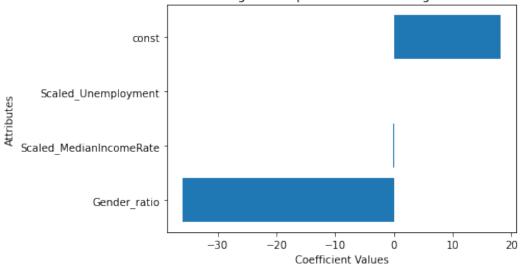
-----

Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Scaled_CrimeCount OLS Least Squares Sun, 11 Dec 2022 16:45:28 132 128 3 nonrobust	F-stati Prob (F	squared:		0.093 0.072 4.372 0.00576 139.17 -270.3 -258.8
0.975]	coef	std err	t	P> t	[0.025
const 30.385	18.1398	6.188	2.931	0.004	5.895
Gender_ratio	-35.9424	12.359	-2.908	0.004	-60.397
Scaled_Unemployment	0.1281	0.049	2.618	0.010	0.031
Scaled_MedianIncomeH-0.044		0.076	-2.566	0.011	-0.344
Omnibus:	173.240				2.156
<pre>Prob(Omnibus):</pre>	0.000	_	Bera (JB):		10191.230
Skew: Kurtosis:	4.738 44.990	Prob(JB Cond. N			0.00 2.26e+03
Kurtosis:			0. ========		

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.26e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Ground Truth:





Our Model:

Linear Model summary:

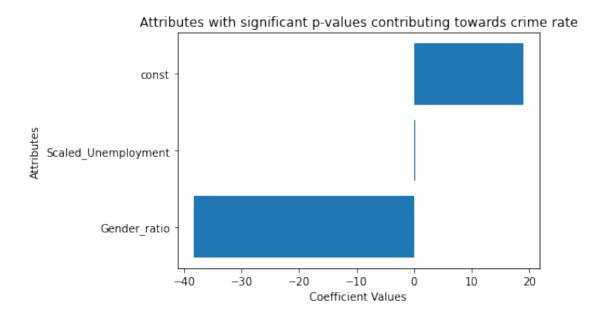
OLS Regression Results

		=====		=======	
Dep. Variable:	Scaled_CrimeCount		-		0.119
Model:	OLS	Adj.	. R-squared:		0.070
Method:	Least Squares	F-st	catistic:		2.401
Date:	Sun, 11 Dec 2022	Prob	(F-statistic	:):	0.0244
Time:	16:45:28	Log-	-Likelihood:		141.12
No. Observations:		AIC:			-266.2
Df Residuals:		BIC:			-243.2
Df Model:	7	210.	•		21012
Covariance Type:	nonrobust				
		coef	std err	t	P> t
[0 005 0 075]		coer	sta err	L	P/
[0.025 0.975]					
	40	0070	2.040	0.004	0.000
const	18.	9070	6.342	2.981	0.003
6.354 31.460					
Gender_ratio	-38.	2771	12.504	-3.061	0.003
-63.026 -13.528					
Scaled_Unemployment	0.	1792	0.062	2.883	0.005
0.056 0.302					
Scaled_MedianIncome	Rate 0.	0345	0.169	0.205	0.838
-0.299 0.368					
WorkforceCount	27.	5330	21.478	1.282	0.202

-14.978	70.044					
PercentNegat	iveUsers	-C	.0811	0.225	-0.360	0.719
-0.527	0.364					
FavorOfDemoc	rats	-C	.8022	0.750	-1.069	0.287
-2.287	0.683					
Scaled_Searc	hCountForDepressi	on -0	.0156	0.038	-0.410	0.682
-0.091	0.060					
========			=======			========
Omnibus:		170.283	Durbin-	-Watson:		2.266
Prob(Omnibus	):	0.000	Jarque-	-Bera (JB	):	9831.650
Skew:		4.600	Prob(J	B):		0.00
Kurtosis:		44.266	Cond. 1	No.		4.38e+03
			=======	=======	========	========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.38e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

OLS Regression Results

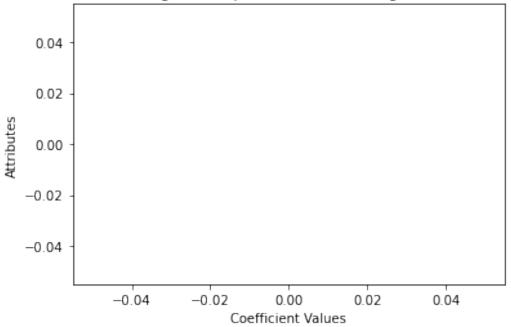
\_\_\_\_\_\_

Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Scaled_CrimeCount OLS Least Squares Sun, 11 Dec 2022 16:45:28 132 127 4 nonrobust	Adj. F-st Prob	R-squared:	c):	0.008 -0.024 0.2467 0.911 133.24 -256.5 -242.1
[0.025 0.975]		coef	std err	t 	P> t
const	-0.	1487	0.592	-0.251	0.802
-1.319 1.022					
WorkforceCount	1.5	2868	5.360	0.240	0.811
-9.320 11.894					
PercentNegativeUser	-0.	1390	0.231	-0.602	0.548
-0.596 0.318					
FavorOfDemocrats	0.4	4476	0.625	0.716	0.475
-0.789 1.684 Scaled_SearchCountF	orDonroggion 0	0149	0.039	0.380	0.704
-0.062 0.092	orbepression 0.	0149	0.039	0.300	0.704
=======================================	=======================================		========		-=======
Omnibus:	193.546	Durb	in-Watson:		1.969
<pre>Prob(Omnibus):</pre>	0.000		ue-Bera (JB)	:	14902.790
Skew:	5.667				0.00
Kurtosis:	53.805		. No.		935.
===========		=====	=======	=======	

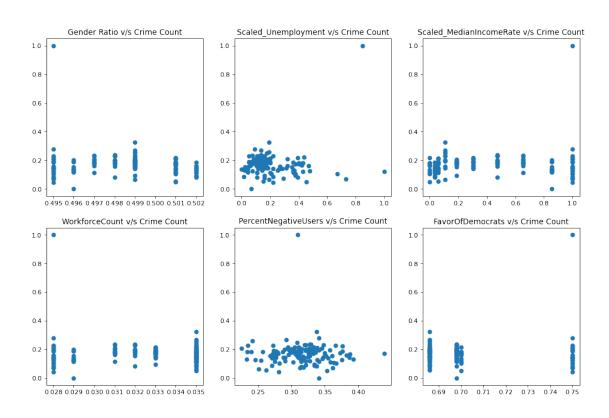
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Plot for Linear Model Coefficients for Our Model without ground truth:

## Attributes with significant p-values contributing towards crime rate



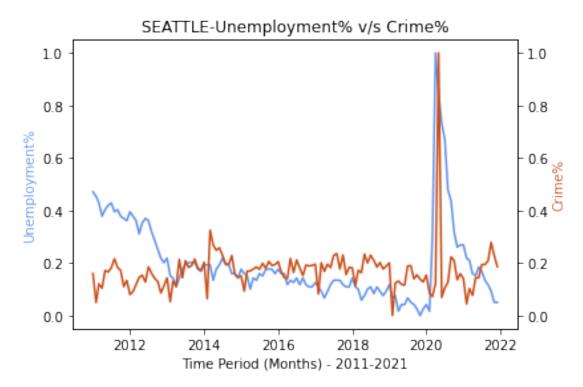
## Correlation Graphs:



/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



DENVER:

Before Covid (Mar-2020)

Ground Truth:

## Linear Model summary:

## OLS Regression Results

=======================================	==========		=========	======	=======
Dep. Variable: Model:	Scaled_CrimeCount OLS	Adj. R	-squared:		0.804 0.798
Method:	Least Squares	F-stat			144.8
Date:	Sun, 11 Dec 2022		F-statistic):		2.41e-37
Time:	16:45:29	•	kelihood:		84.786
No. Observations:	110	AIC:			-161.6
Df Residuals:	106	BIC:			-150.8
Df Model:	3				
Covariance Type:	nonrobust				
		======	========	======	=======
	coef	std err	t	P> t	[0.025
0.975]	6061	Sou ell	Ü	17   6	[0.020
const	-2.9581	13.854	-0.214	0.831	-30.425
24.509					
Gender_ratio	5.5403	27.692	0.200	0.842	-49.361
60.442					
Scaled_Unemployment 0.569	0.3660	0.103	3.566	0.001	0.163
Scaled_MedianIncomeF 1.304	Rate 1.1174	0.094	11.901	0.000	0.931
				======	
Omnibus:	45.501	Durbin	-Watson:		0.392
<pre>Prob(Omnibus):</pre>	0.000	Jarque	-Bera (JB):		187.698
Skew:	-1.327	Prob(J	B):		1.75e-41
Kurtosis:	8.823	Cond.	No.		3.40e+03
=======================================			========		=======

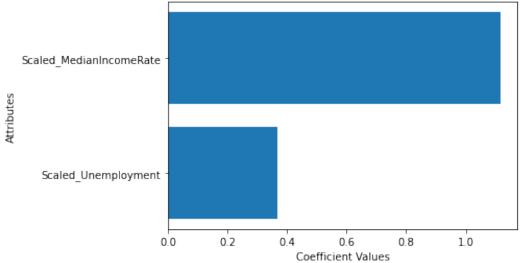
#### Notes:

Plot for Linear Model Coefficients for Ground Truth:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 3.4e+03. This might indicate that there are strong multicollinearity or other numerical problems.





Our Model:

Linear Model summary:

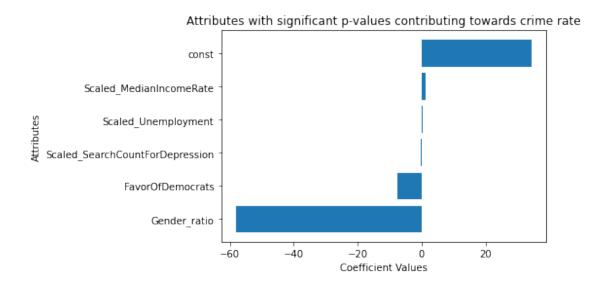
OLS Regression Results

=======================================	=============	=====		=======	========
Dep. Variable:	Scaled_CrimeCount	-			0.891
Model:	OLS	Adj.	R-squared:		0.884
Method:	Least Squares	F-st	atistic:		119.6
Date:	Sun, 11 Dec 2022	Prob	(F-statisti	c):	3.04e-46
Time:	16:45:29	Log-	Likelihood:		117.32
No. Observations:	110	AIC:			-218.6
Df Residuals:	102	BIC:			-197.0
Df Model:	7				
Covariance Type:	nonrobust				
	===========	=====	=======	=======	=========
		coef	std err	t	P> t
[0.025 0.975]					
const	34.	4739	12.006	2.871	0.005
10.660 58.288					
Gender_ratio	-58.	1437	23.386	-2.486	0.015
-104.530 -11.75	8				
Scaled_Unemployment	0.	4250	0.088	4.825	0.000
0.250 0.600					
Scaled_MedianIncome	Rate 1.	2283	0.074	16.706	0.000
1.082 1.374					
WorkforceCount	3.	6717	3.239	1.134	0.260

-2.752	10.096					
PercentNega	tiveUsers	-0.1	.995	0.247	-0.806	0.422
-0.690	0.291					
FavorOfDemo	crats	-7.6	505	1.039	-7.361	0.000
-9.712	-5.589					
Scaled_Sear	${\tt chCountForDepression}$	n -0.2	2229	0.046	-4.805	0.000
-0.315	-0.131					
========						========
Omnibus:		3.928	Durbin-	Watson:		0.494
Prob(Omnibu	s):	0.140	Jarque-	Bera (JB)	:	2.188
Skew:		-0.021	Prob(JB	3):		0.335
Kurtosis:		2.310	Cond. N	lo.		4.84e+03
========	=======================================	=======	=======	.=======	========	========

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.84e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

OLS Regression Results

Dep. Variable: Scaled\_CrimeCount R-squared: 0.277

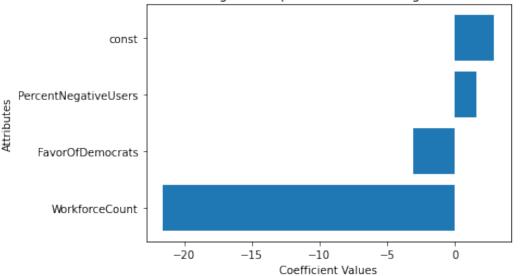
Model: 0LS Adj. R-squared: 0.254

Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Least Squares Sun, 11 Dec 2022 16:45:29 132 127 4 nonrobust	Prob Log-1 AIC: BIC:	(F-statisti Likelihood:		12.16 2.12e-08 26.188 -42.38 -27.96
[0.025 0.975]		coef	std err	t 	P> t
const	2	.9093	0.682	4.268	0.000
1.560 4.258					
WorkforceCount	-21	. 5788	6.051	-3.566	0.001
-33.553 -9.605					
PercentNegativeUsers	1	.5894	0.446	3.564	0.001
0.707 2.472					
FavorOfDemocrats	-3	.0935	0.843	-3.669	0.000
-4.762 -1.425		0740	0.000	0.054	0.005
Scaled_SearchCountFo	rDepression 0	.0762	0.089	0.854	0.395
-0.100 0.253					
Omnibus:	13.018	Durb	in-Watson:		0.272
Prob(Omnibus):	0.001		ie-Bera (JB)	•	13.886
Skew:		Prob		-	0.000966
Kurtosis:	3.382	Cond			472.
	===========				=======

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

Plot for Linear Model Coefficients for Our Model without ground truth:

## Attributes with significant p-values contributing towards crime rate



## Till Dec-2021

Ground Truth:

Linear Model summary:

## OLS Regression Results

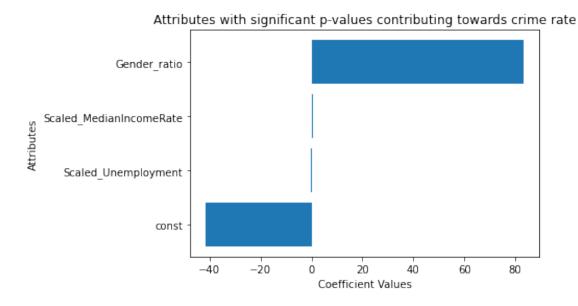
Dep. Variable:	Scaled_CrimeCount	R-squ	ared:		0.596
Model:	OLS	Adj.	R-squared:		0.586
Method:	Least Squares	F-sta	tistic:		62.89
Date:	Sun, 11 Dec 2022	Prob	(F-statistic):		4.69e-25
Time:	16:45:29	Log-L	ikelihood:		64.567
No. Observations:	132	AIC:			-121.1
Df Residuals:	128	BIC:			-109.6
Df Model:	3				
Covariance Type:	nonrobust				
=======					
	coef	std err	t	P> t	[0.025
0.975]					
const	-41.3537	9.626	-4.296	0.000	-60.401
-22.306					
Gender_ratio	83.1072	19.225	4.323	0.000	45.067
121.147					
${\tt Scaled\_Unemployment}$	-0.3693	0.067	-5.484	0.000	-0.503

-0	2	3	6
-0	_	J	u

Scaled_MedianIncomeRate 0.689	0.5486	0.071	7.724	0.000	0.408
=======================================	========			========	=======
Omnibus:	3.288	Durbin-Wa	tson:		0.248
Prob(Omnibus):	0.193	Jarque-Be	ra (JB):		2.970
Skew:	0.366	Prob(JB):			0.227
Kurtosis:	3.072	Cond. No.			2.02e+03

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.02e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Ground Truth:



Our Model: Linear Model summary:

#### OLS Regression Results

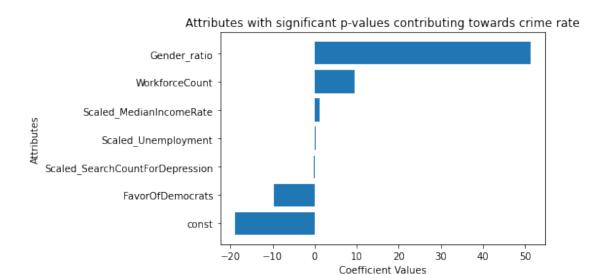
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.807
Model:	OLS	Adj. R-squared:	0.796
Method:	Least Squares	F-statistic:	73.99
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	3.08e-41
Time:	16:45:29	Log-Likelihood:	113.30

No. Observations:  Df Residuals:  Df Model:  Covariance Type:	132 124 7 onrobust	AIC: BIC:			-210.6 -187.5
		======			
		coef	std err	t	P> t
[0.025 0.975]					
const	-18.	9525	8.401	-2.256	0.026
-35.580 -2.325					
Gender_ratio	51.	3957	16.213	3.170	0.002
19.306 83.485					
Scaled_Unemployment	0.	1716	0.073	2.357	0.020
0.028 0.316					
Scaled_MedianIncomeRate	1.	1022	0.074	14.974	0.000
0.957 1.248					
WorkforceCount	9.	4968	3.816	2.489	0.014
1.944 17.049					
PercentNegativeUsers	-0.	1267	0.257	-0.492	0.624
-0.636 0.383					
FavorOfDemocrats	-9.	6450	0.900	-10.722	0.000
-11.425 -7.865					
Scaled_SearchCountForDepression	on -0.	1330	0.049	-2.715	0.008
-0.230					
Omnibus:			in-Watson:		0.273
<pre>Prob(Omnibus):</pre>	0.000		ie-Bera (JB)	):	9.581
Skew:		Prob			0.00831
Kurtosis:	1.990	Cond.			3.08e+03
		======			

Plot for Linear Model Coefficients for Our Model:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 3.08e+03. This might indicate that there are strong multicollinearity or other numerical problems.



Our Model without ground truth: Linear Model summary:

# OLS Regression Results

Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	OLS Least Squares Sun, 11 Dec 2022	Adj. F-st Prob Log- AIC: BIC:	R-squared: atistic: (F-statisti Likelihood:	c):	0.277 0.254 12.16 2.12e-08 26.188 -42.38 -27.96
[0.025 0.975]		coef	std err	t	P> t
const 1.560 4.258 WorkforceCount -33.553 -9.605 PercentNegativeUser	-21 5	.9093 .5788	0.682 6.051 0.446	-3.566	0.000 0.001 0.001
0.707 2.472  FavorOfDemocrats -4.762 -1.425  Scaled_SearchCountF -0.100 0.253	-3	.0935	0.843		0.000

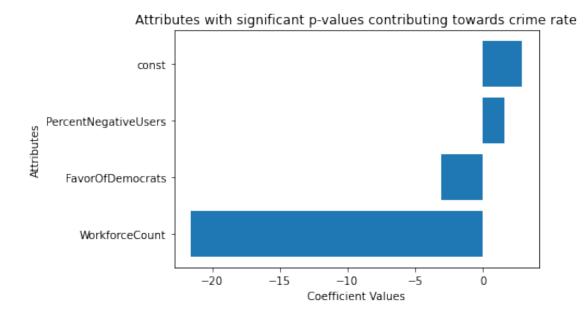
=======================================			=========
Omnibus:	13.018	Durbin-Watson:	0.272
Prob(Omnibus):	0.001	Jarque-Bera (JB):	13.886
Skew:	0.771	Prob(JB):	0.000966
Kurtosis:	3.382	Cond. No.	472.

\_\_\_\_\_

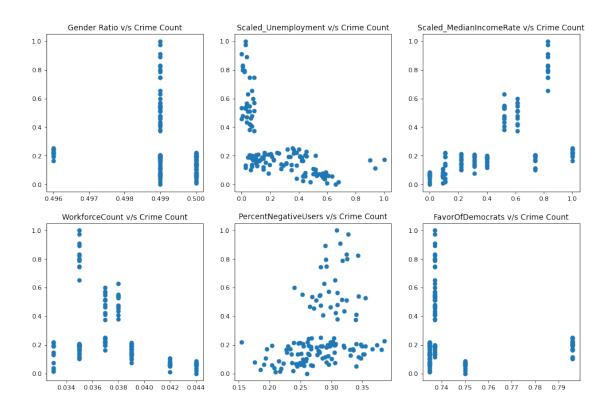
#### Notes:

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

Plot for Linear Model Coefficients for Our Model without ground truth:



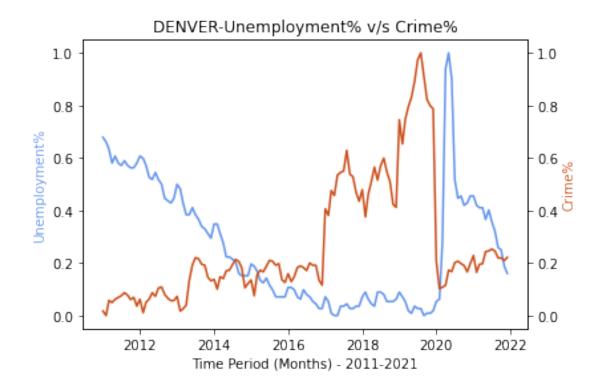
Correlation Graphs:



/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



## DALLAS:

Before Covid (Mar-2020)

Ground Truth:

Linear Model summary:

## OLS Regression Results

=======================================			
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.527
Model:	OLS	Adj. R-squared:	0.505
Method:	Least Squares	F-statistic:	24.10
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	1.33e-10
Time:	16:45:30	Log-Likelihood:	41.919
No. Observations:	69	AIC:	-75.84
Df Residuals:	65	BIC:	-66.90
Df Model:	3		
Covariance Type:	nonrobust		
=======================================			
========			- I. I. Fa aa-

 $\texttt{coef} \qquad \texttt{std err} \qquad \qquad \texttt{t} \qquad \texttt{P>|t|} \qquad \texttt{[0.025]}$ 

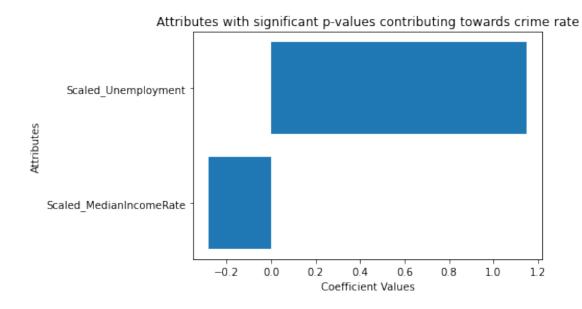
## 0.975]

const	4.5994	3.188	1.443	0.154	-1.768
10.967					
Gender_ratio	-8.1077	6.305	-1.286	0.203	-20.700
4.485	1.1476	0.433	2.653	0.010	0.284
Scaled_Unemployment 2.012	1.1470	0.433	2.003	0.010	0.204
Scaled MedianIncomeRate	-0.2790	0.093	-2.999	0.004	-0.465
-0.093					
	========		========	=======	======
Omnibus:	8.945	Durbin-	Watson:		0.873
<pre>Prob(Omnibus):</pre>	0.011	Jarque-	Bera (JB):		10.962
Skew:	0.544	Prob(JB	):		0.00416
Kurtosis:	4.622	Cond. N	ο.		524.
=======================================		=======	========	=======	=======

## Notes:

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

Plot for Linear Model Coefficients for Ground Truth:



## Our Model: Linear Model summary:

OLS Regression Results

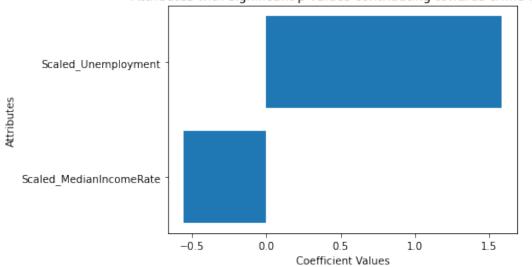
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Scaled_CrimeCount OLS Least Squares Sun, 11 Dec 2022 16:45:36	Adj F-s Pro D Log AIC 1 BIC		ic):	0.563 0.513 11.24 4.76e-09 44.706 -73.41 -55.54
		coef	std err	t	P> t
[0.025 0.975]					
	-				
const	-[	5.3942	5.639	-0.957	0.343
-16.671 5.883	3				
Gender_ratio		5.5236	9.218	0.708	0.482
-11.909 24.956					
Scaled_Unemployment	;	1.5814	0.512	3.086	0.003
0.557 2.606	D .		0.450	0. 400	0.004
Scaled_MedianIncome	eKate -(	0.5540	0.159	-3.488	0.001
-0.871 -0.236 WorkforceCount	20	0.1947	19.269	1.567	0.122
-8.335 68.725	30	J. 1341	19.209	1.507	0.122
PercentNegativeUser	rg (	0.0567	0.268	0.212	0.833
-0.479 0.592			0.200	0.212	0.000
FavorOfDemocrats	;	3.4560	1.939	1.783	0.080
-0.421 7.333					
Scaled_SearchCountF	orDepression (	0.1059	0.123	0.859	0.394
-0.140 0.352					
		====== 1 Dur	:======== :bin-Watson:	========	0.999
Prob(Omnibus):	0.249	9 Jar	que-Bera (JB	3):	2.168
Skew:	0.19		b(JB):		0.338
Kurtosis:	3.77	4 Con	nd. No.		1.75e+03
			.=======	========	========

Plot for Linear Model Coefficients for Our Model:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 1.75e+03. This might indicate that there are strong multicollinearity or other numerical problems.





Our Model without ground truth: Linear Model summary:

OLS Regression Results

============	===========	=====	=====	=========	========	========
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Least Squa Sun, 11 Dec 2 16:48	OLS ares 2022 5:30 91 86 4	Adj. F-st Prob		c):	0.375 0.346 12.91 2.81e-08 36.864 -63.73 -51.17
	=========	=====		=======		
[0.025 0.975]			coef	std err	t	P> t
const		3.0	0907	0.427	7.240	0.000
2.242 3.939 WorkforceCount -26.807 18.809		-3.9	9987	11.473	-0.349	0.728
PercentNegativeUser -1.105 0.108		-0.4	4985	0.305	-1.633	0.106
FavorOfDemocrats -5.668 -2.057		-3.8	3625	0.908	-4.252	0.000
Scaled_SearchCountF	orDepression	-0.1	1874	0.098	-1.906	0.060

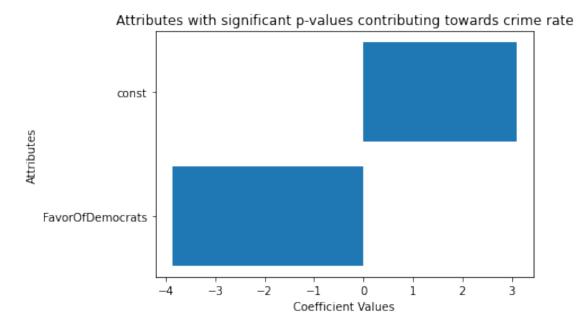
#### -0.383 0.008

	=======		
Omnibus:	9.059	Durbin-Watson:	0.824
<pre>Prob(Omnibus):</pre>	0.011	Jarque-Bera (JB):	9.005
Skew:	0.638	Prob(JB):	0.0111
Kurtosis:	3.863	Cond. No.	831.

#### Notes:

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

Plot for Linear Model Coefficients for Our Model without ground truth:



Till Dec-2021

#### Ground Truth:

Linear Model summary:

OLS Regression Results

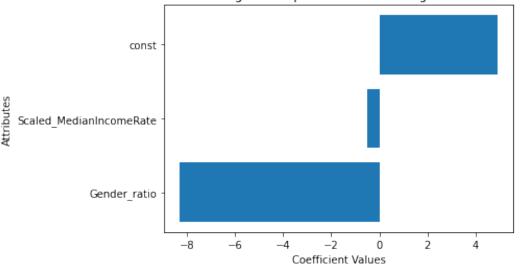
============			=========
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.519
Model:	OLS	Adj. R-squared:	0.503
Method:	Least Squares	F-statistic:	31.32

Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Sun,	11 Dec 2022 16:45:30 91 87 3 nonrobust	Log-Li L AIC: BIC:	F-statistic): kelihood:		7.99e-14 48.780 -89.56 -79.52
=======		coef	std err		D> +	[0 025
0.975]		coei	sta err	t 	P> t	[0.025
const		4.9098	2.009	2.444	0.017	0.917
8.903						
Gender_ratio -0.413		-8.2919	3.964	-2.092	0.039	-16.170
Scaled_Unemployment 0.102		-0.0628	0.083	-0.758	0.451	-0.228
Scaled_MedianIncomeR -0.392	ate 	-0.4986	0.054	-9.288	0.000	-0.605
Omnibus:		0.862	2 Durbin	-Watson:		0.976
<pre>Prob(Omnibus):</pre>		0.650	) Jarque	-Bera (JB):		0.883
Skew:		0.224	Prob(J	B):		0.643
Kurtosis:		2.822	Cond.	No.		372.

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

Plot for Linear Model Coefficients for Ground Truth:





Our Model: Linear Model summary:

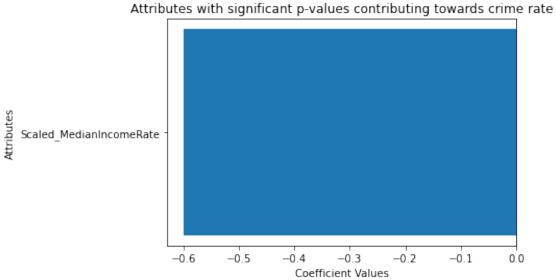
OLS Regression Results

Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Scaled_CrimeCount OLS Least Squares Sun, 11 Dec 2022 16:45:30 91 83 7 nonrobust	Adj. R-square F-statistic:	stic):	0.526 0.486 13.17 2.70e-11 49.448 -82.90 -62.81
[0.025 0.975]		coef std err	t	P> t
const -8.360 10.665		1522 4.783 9348 7.844		0.810
Gender_ratio -17.536 13.667 Scaled_Unemployment -0.248 0.143		9348 7.844 0528 0.098		0.806
Scaled_MedianIncome -0.921 -0.277 WorkforceCount		<ul><li>5992 0.162</li><li>0799 18.777</li></ul>		0.000

-17.268	57.427					
PercentNegat	iveUsers	-0.0	286	0.288	-0.099	0.921
-0.601	0.544					
FavorOfDemoc	rats	0.3	751	1.605	0.234	0.816
-2.817	3.567					
Scaled_Searc	${\tt hCountForDepression}$	0.0	880	0.095	0.092	0.927
-0.181	0.198					
		======	======			
Omnibus:		0.604	Durbin-	Watson:		0.995
Prob(Omnibus	):	0.739	Jarque-	Bera (JB)	:	0.741
Skew:		0.159	Prob(JB	):		0.690
Kurtosis:		2.692	Cond. N	ο.		1.95e+03
========		======	======	=======		

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.95e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

OLS Regression Results

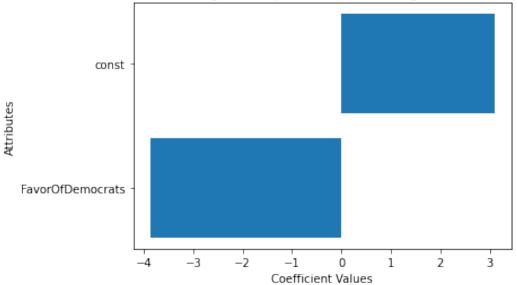
Dep. Variable: Scaled\_CrimeCount R-squared: 0.375

Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	OLS Least Squares Sun, 11 Dec 2022 16:45:30 91 86 4 nonrobust	F-st Prob	R-squared: atistic: (F-statist: Likelihood:	ic):	0.346 12.91 2.81e-08 36.864 -63.73 -51.17
[0.025 0.975]		coef	std err	t	P> t
const	3.	0907	0.427	7.240	0.000
2.242 3.939 WorkforceCount	-3.	9987	11.473	-0.349	0.728
-26.807 18.809 PercentNegativeUsers	-O.	4985	0.305	-1.633	0.106
-1.105 0.108 FavorOfDemocrats	-3.	8625	0.908	-4.252	0.000
-5.668 -2.057 Scaled_SearchCountFo	•	1874	0.098	-1.906	0.060
Omnibus:	9.059	Durb	======== in-Watson:		0.824
<pre>Prob(Omnibus):</pre>	0.011	Jarq	ue-Bera (JB)	):	9.005
Skew:	0.638	Prob	(JB):		0.0111
Kurtosis:	3.863		. No.		831.
=======================================		:=====	=======		========

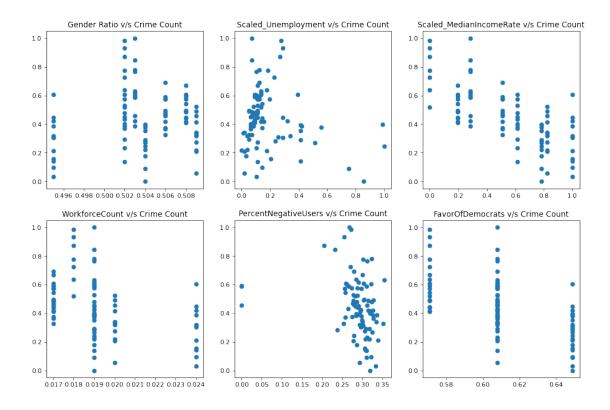
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Plot for Linear Model Coefficients for Our Model without ground truth:





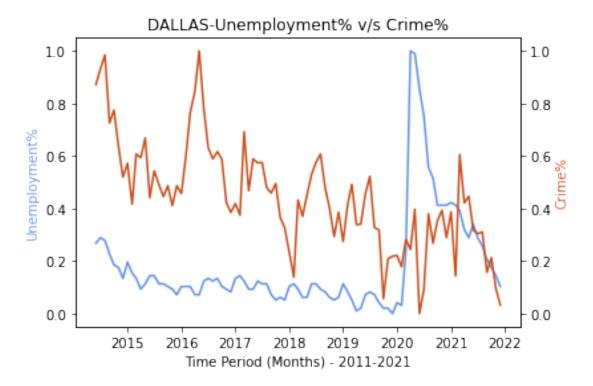
### Correlation Graphs:



/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



NEW\_ORLEANS:

Before Covid (Mar-2020)

Ground Truth:

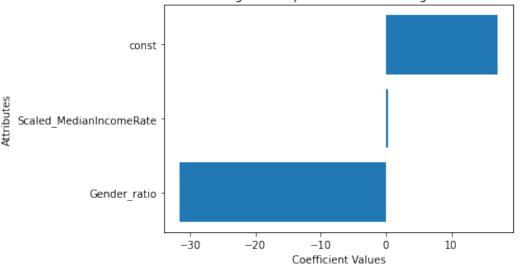
Linear Model summary:

Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Scaled_CrimeCount OLS Least Squares Sun, 11 Dec 2022 16:45:31 110 106 3 nonrobust	Adj. R-F-stati Prob (F Log-Lik AIC: BIC:	squared:		0.174 0.150 7.432 0.000145 58.774 -109.5 -98.75
0.975]	coef	std err	t	P> t	[0.025
const 25.822	17.0589	4.420	3.859	0.000	8.296
Gender_ratio	-31.5360	8.437	-3.738	0.000	-48.262
Scaled_Unemployment 0.364	-0.2596	0.314	-0.826	0.411	-0.883
Scaled_MedianIncome 0.490		0.080	4.118	0.000	0.171
Omnibus: Prob(Omnibus): Skew: Kurtosis:	59.259 0.000 -1.756 10.097	Durbin- Jarque- Prob(JE Cond. N	Bera (JB):		0.799 287.392 3.92e-63 802.

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

Plot for Linear Model Coefficients for Ground Truth:





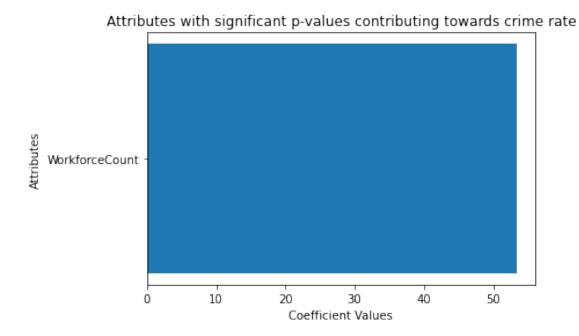
Our Model: Linear Model summary:

Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Scaled_CrimeCount OLS Least Squares Sun, 11 Dec 2022 16:45:31 110 102 7 nonrobust	R-so Adj. F-st Prob Log- AIC: BIC:	quared: R-squared: atistic: (F-statisti -Likelihood:		0.309 0.262 6.526 2.29e-06 68.629 -121.3 -99.65
[0.025 0.975]		coef	std err	t	P> t
const -23.703 6.859 Gender_ratio		4221 3918	7.704 12.625	-1.093 0.902	0.277
-13.649 36.433 Scaled_Unemployment -0.777 0.442		1678	0.307	-0.546	0.586
Scaled_MedianIncome -0.304 0.193 WorkforceCount		0557 3968	0.125 13.820	-0.444 3.864	0.658

25.985 80.	. 809					
PercentNegative	eUsers	-0.0	741	0.124	-0.597	0.552
-0.320 0.	. 172					
FavorOfDemocrat	ts	0.4	838	4.173	0.116	0.908
-7.793 8.	.761					
Scaled_SearchCo	${\tt ountForDepression}$	-0.0	944	0.105	-0.903	0.369
-0.302 0.	. 113					
==========		======				
Omnibus:		63.824	Durbin-V	Watson:		1.000
<pre>Prob(Omnibus):</pre>		0.000	Jarque-l	Bera (JB):		381.243
Skew:		-1.827	Prob(JB)	):		1.64e-83
Kurtosis:		11.356	Cond. No	ο.		2.14e+03
		======				

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.14e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Plot for Linear Model Coefficients for Our Model:



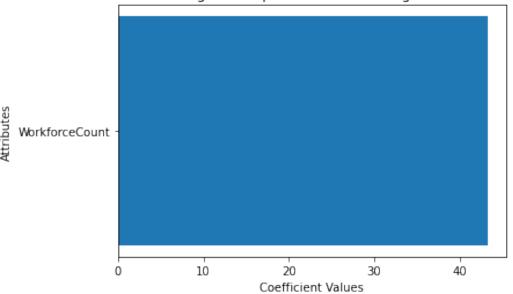
Our Model without ground truth: Linear Model summary:

					========
Dep. Variable:	${\tt Scaled\_CrimeCount}$	R-so	quared:		0.346
Model:	OLS	Adj	. R-squared:		0.325
Method:	Least Squares	F-st	tatistic:		16.79
Date:	Sun, 11 Dec 2022	Prol	o (F-statisti	c):	4.54e-11
Time:	16:45:31	Log-	-Likelihood:		82.423
No. Observations:	132	AIC	:		-154.8
Df Residuals:	127	BIC	:		-140.4
Df Model:	4				
Covariance Type:	nonrobust				
=======================================	=======================================			========	========
=======================================					
		coef	std err	t	P> t
[0.025 0.975]					
		4500	4 504	0.700	0.440
const	-1.	1539	1.501	-0.769	0.443
-4.123 1.816	40	0006	7 710	F C11	0.000
WorkforceCount	43.	2886	7.716	5.611	0.000
28.021 58.556		0025	0 115	0.020	0.076
PercentNegativeUser -0.231 0.224	'S -0.	0035	0.115	-0.030	0.976
	0	6406	1 400	-0.435	0 664
FavorOfDemocrats -3.602 2.303	-0.	6496	1.492	-0.435	0.664
Scaled_SearchCountF	orDonroggion 0	0483	0.077	0.630	0.530
-0.103 0.200	ordepression o.	0403	0.077	0.030	0.550
-0.105 0.200					
Omnibus:	49.530	Durl	oin-Watson:		1.008
Prob(Omnibus):	0.000		que-Bera (JB)		190.272
Skew:	-1.297		que Beru (3B) o(JB):	•	4.82e-42
Kurtosis:	8.279		d. No.		944.
=======================================			 	========	

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

Plot for Linear Model Coefficients for Our Model without ground truth:

# Attributes with significant p-values contributing towards crime rate



#### Till Dec-2021

Ground Truth:

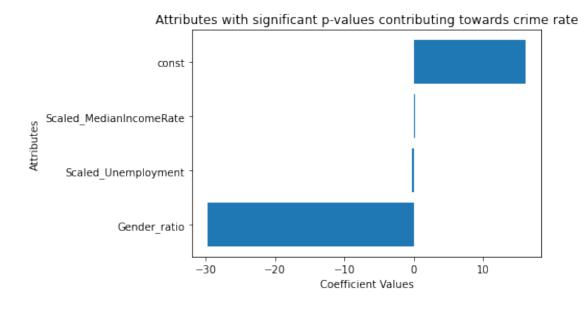
Linear Model summary:

=======================================		======	 :===========	=======	=======
Dep. Variable:	Scaled_CrimeCount	R-squ	ared:		0.190
Model:	OLS	Adj.	R-squared:		0.171
Method:	Least Squares	F-sta	tistic:		10.01
Date:	Sun, 11 Dec 2022	Prob	(F-statistic):		5.68e-06
Time:	16:45:31	Log-L	ikelihood:		68.319
No. Observations:	132	AIC:			-128.6
Df Residuals:	128	BIC:			-117.1
Df Model:	3				
Covariance Type:	nonrobust				
========					
	coef	std err	t	P> t	[0.025
0.975]					
const	16.1179	3.407	4.731	0.000	9.377
22.858					
Gender_ratio	-29.6911	6.558	3 -4.528	0.000	-42.667
-16.716					

Scaled_Unemployment	-0.2674	0.084	-3.171	0.002	-0.434
-0.101	0.2052	0.069	2.953	0.004	0.068
Scaled_MedianIncomeRate 0.343	0.2052	0.069	2.955	0.004	0.068
=======================================				=======	======
Omnibus:	33.459	Durbin-V	Natson:		0.765
Prob(Omnibus):	0.000	<pre>Jarque-Bera (JB):</pre>		83.602	
Skew:	-0.984	Prob(JB):		7.02e-19	
Kurtosis:	6.366	Cond. No	· .	699.	
=======================================	==========			========	======

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

Plot for Linear Model Coefficients for Ground Truth:



## Our Model: Linear Model summary:

Dep. Variable:	Scaled_CrimeCount	R-squared:	0.367
Model:	OLS	Adj. R-squared:	0.331
Method:	Least Squares	F-statistic:	10.26
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	4.28e-10
Time:	16:45:31	Log-Likelihood:	84.559
No. Observations:	132	AIC:	-153.1

Df Residuals: 12	4 BIC: -130	1
------------------	-------------	---

Df Model: 7
Covariance Type: nonrobust

coef std err t P> t   [0.025 0.975]	Covariance	: Type:	nonrobust 				
-23.655 3.363  Gender_ratio 16.1323 10.553 1.529 0.129 -4.755 37.020  Scaled_Unemployment -0.0304 0.089 -0.343 0.732 -0.206 0.145  Scaled_MedianIncomeRate -0.0911 0.114 -0.795 0.428 -0.318 0.136  WorkforceCount 55.2672 13.302 4.155 0.000 28.940 81.595  PercentNegativeUsers -0.0470 0.117 -0.403 0.688 -0.278 0.184  FavorOfDemocrats -0.6228 3.539 -0.176 0.861 -7.627 6.381  Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141	=======			oef	std err	t	P> t
-23.655 3.363  Gender_ratio 16.1323 10.553 1.529 0.129 -4.755 37.020  Scaled_Unemployment -0.0304 0.089 -0.343 0.732 -0.206 0.145  Scaled_MedianIncomeRate -0.0911 0.114 -0.795 0.428 -0.318 0.136  WorkforceCount 55.2672 13.302 4.155 0.000 28.940 81.595  PercentNegativeUsers -0.0470 0.117 -0.403 0.688 -0.278 0.184  FavorOfDemocrats -0.6228 3.539 -0.176 0.861 -7.627 6.381  Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141	const		-10 1	45Q	6 825	_1 /187	0 1/10
Gender_ratio 16.1323 10.553 1.529 0.129 -4.755 37.020 Scaled_Unemployment -0.0304 0.089 -0.343 0.732 -0.206 0.145 Scaled_MedianIncomeRate -0.0911 0.114 -0.795 0.428 -0.318 0.136 WorkforceCount 55.2672 13.302 4.155 0.000 28.940 81.595 PercentNegativeUsers -0.0470 0.117 -0.403 0.688 -0.278 0.184 FavorOfDemocrats -0.6228 3.539 -0.176 0.861 -7.627 6.381 Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141		3 363	10.1	100	0.020	1.407	0.140
-4.755 37.020 Scaled_Unemployment -0.0304 0.089 -0.343 0.732 -0.206 0.145 Scaled_MedianIncomeRate -0.0911 0.114 -0.795 0.428 -0.318 0.136 WorkforceCount 55.2672 13.302 4.155 0.000 28.940 81.595 PercentNegativeUsers -0.0470 0.117 -0.403 0.688 -0.278 0.184 FavorOfDemocrats -0.6228 3.539 -0.176 0.861 -7.627 6.381 Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141			16.1	323	10.553	1.529	0.129
-0.206	_			0_0	201000	2.020	0.120
Scaled_MedianIncomeRate       -0.0911       0.114       -0.795       0.428         -0.318       0.136         WorkforceCount       55.2672       13.302       4.155       0.000         28.940       81.595         PercentNegativeUsers       -0.0470       0.117       -0.403       0.688         -0.278       0.184         FavorOfDemocrats       -0.6228       3.539       -0.176       0.861         -7.627       6.381         Scaled_SearchCountForDepression       -0.0381       0.090       -0.422       0.674         -0.217       0.141	Scaled_Une	employment	-0.0	304	0.089	-0.343	0.732
-0.318	-0.206	0.145					
WorkforceCount 55.2672 13.302 4.155 0.000 28.940 81.595  PercentNegativeUsers -0.0470 0.117 -0.403 0.688 -0.278 0.184  FavorOfDemocrats -0.6228 3.539 -0.176 0.861 -7.627 6.381  Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141	Scaled_Med	lianIncomeRate	-0.09	911	0.114	-0.795	0.428
28.940 81.595  PercentNegativeUsers -0.0470 0.117 -0.403 0.688 -0.278 0.184  FavorOfDemocrats -0.6228 3.539 -0.176 0.861 -7.627 6.381  Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141	-0.318	0.136					
PercentNegativeUsers -0.0470 0.117 -0.403 0.688 -0.278 0.184 FavorOfDemocrats -0.6228 3.539 -0.176 0.861 -7.627 6.381 Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141	WorkforceC	Count	55.20	672	13.302	4.155	0.000
-0.278	28.940	81.595					
FavorOfDemocrats -0.6228 3.539 -0.176 0.861 -7.627 6.381	PercentNeg	gativeUsers	-0.04	470	0.117	-0.403	0.688
-7.627 6.381 Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141	-0.278	0.184					
Scaled_SearchCountForDepression -0.0381 0.090 -0.422 0.674 -0.217 0.141		ocrats	-0.6	228	3.539	-0.176	0.861
-0.217 0.141							
	<del>-</del>	•	ion -0.03	381	0.090	-0.422	0.674
	V	***					
				===== Durbir	======= 1-Watson:		1.035
Prob(Omnibus): 0.000 Jarque-Bera (JB): 291.185	_	ous):				):	
Skew: -1.484 Prob(JB): 5.89e-64				-		•	
Kurtosis: 9.643 Cond. No. 2.25e+03	Kurtosis:						

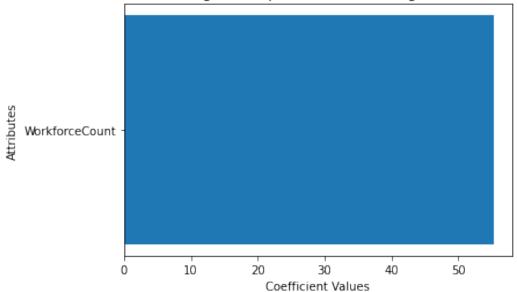
#### Notes:

Plot for Linear Model Coefficients for Our Model:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

<sup>[2]</sup> The condition number is large, 2.25e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Attributes with significant p-values contributing towards crime rate



Our Model without ground truth:

Linear Model summary:

OLS Regression Results

Dep. Variable:	Scaled_CrimeCount	R-squared:		0.346
Model:	OLS	Adj. R-squared:		0.325
Method:	Least Squares	F-statistic:		16.79
Date:	Sun, 11 Dec 2022	Prob (F-statisti	c):	4.54e-11
Time:	16:45:31	Log-Likelihood:		82.423
No. Observations:	132	AIC:		-154.8
Df Residuals:	127	BIC:		-140.4
Df Model:	4			
Covariance Type:	nonrobust			
=======================================		==========		========
=======================================		coef std err	t.	P> t
[0.025 0.975]		coel sta err	L	P> U
[0.025 0.575]				
const	-1.	1539 1.501	-0.769	0.443
-4.123 1.816				
WorkforceCount	43.	2886 7.716	5.611	0.000
28.021 58.556				
PercentNegativeUser	-O.	0035 0.115	-0.030	0.976
-0.231 0.224				
FavorOfDemocrats	-0.	6496 1.492	-0.435	0.664
-3.602 2.303				

Scaled_SearchCountForDepression	on 0.0	0.077	0.630	0.530
-0.103 0.200				
=======================================				
Omnibus:	49.530	Durbin-Watson:		1.008
<pre>Prob(Omnibus):</pre>	0.000	Jarque-Bera (JB):		190.272
Skew:	-1.297	<pre>Prob(JB):</pre>		4.82e-42
Kurtosis:	8.279	Cond. No.		944.
	:======		=======	========

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

Plot for Linear Model Coefficients for Our Model without ground truth:

WorkforceCount - Attributes with significant p-values contributing towards crime rate

20

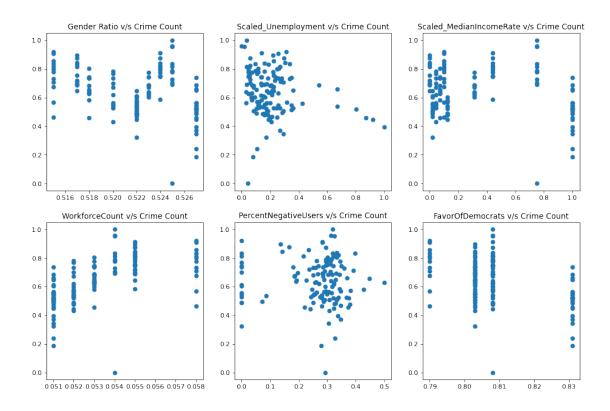
Coefficient Values

30

40

10

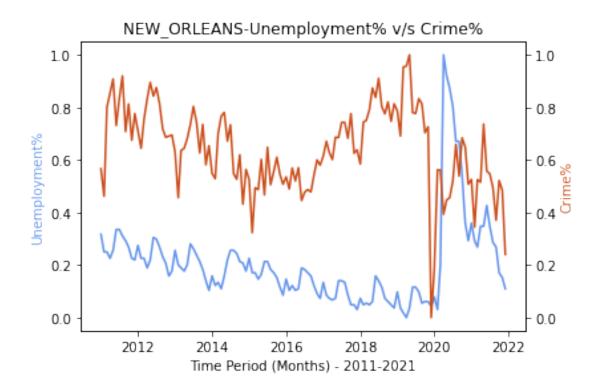
### Correlation Graphs:



/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

<Figure size 2400x1200 with 0 Axes>



#### INDIANAPOLIS:

Before Covid (Mar-2020)

Ground Truth:

Linear Model summary:

### OLS Regression Results

=======================================			
Dep. Variable:	Scaled_CrimeCount	R-squared:	0.566
Model:	OLS	Adj. R-squared:	0.554
Method:	Least Squares	F-statistic:	46.13
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	3.71e-19
Time:	16:45:32	Log-Likelihood:	80.659
No. Observations:	110	AIC:	-153.3
Df Residuals:	106	BIC:	-142.5
Df Model:	3		
Covariance Type:	nonrobust		
=======================================			
========			

coef std err t P>|t| [0.025]

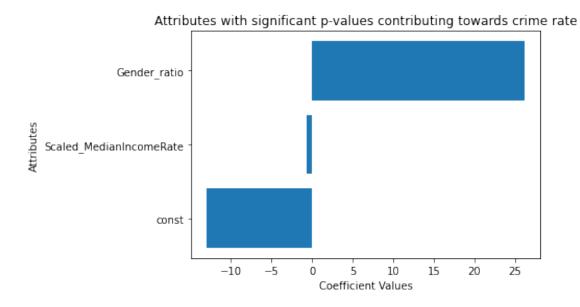
### 0.975]

const	-12.9353	2.881	-4.490	0.000	-18.647
-7.224					
Gender_ratio	26.1183	5.583	4.678	0.000	15.050
37.186					
Scaled_Unemployment	-0.0185	0.111	-0.166	0.868	-0.239
0.202	-0.6882	0.124	-5.550	0.000	-0.934
Scaled_MedianIncomeRate -0.442	-0.0002	0.124	-5.550	0.000	-0.934
-0.442	===========	=======		========	======
Omnibus:	3.462	Durbin-	-Watson:		0.711
Prob(Omnibus):	0.177	Jarque-	Bera (JB):		3.221
Skew:	-0.211	Prob(JE	3):		0.200
Kurtosis:	3.725	Cond. N	lo.		668.
			========	========	======

#### Notes:

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

Plot for Linear Model Coefficients for Ground Truth:

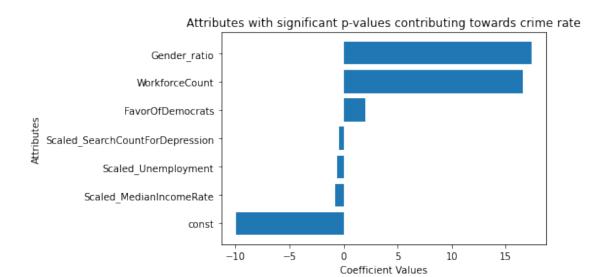


# Our Model: Linear Model summary:

OLS Regression Results

Model: Method:	led_CrimeCount OLS Least Squares n, 11 Dec 2022 16:45:32 110 102 7 nonrobust	Adj. F-st Prob		c):	0.763 0.747 46.87 4.20e-29 113.86 -211.7 -190.1
[0.025 0.975]		coef	std err	t	P> t
const	-9.	9486	2.314	-4.299	0.000
-14.538 -5.359					
Gender_ratio	17.	3994	4.714	3.691	0.000
8.050 26.749	0	E440	0 110	4 504	0.000
Scaled_Unemployment -0.780 -0.309	-0.	5442	0.119	-4.584	0.000
Scaled_MedianIncomeRate -0.948 -0.546	-0.	7472	0.101	-7.368	0.000
WorkforceCount	16.	5675	4.442	3.730	0.000
7.757 25.378					
PercentNegativeUsers	0.	1508	0.130	1.157	0.250
-0.108 0.409					
FavorOfDemocrats	2.	0264	0.746	2.718	0.008
0.547 3.505 Scaled_SearchCountForDe -0.471 -0.281		3757	0.048	-7.860	0.000
Omnibus:	2.641		in-Watson:		1.230
Prob(Omnibus):	0.267		ue-Bera (JB)	:	2.280
Skew:	-0.149	-	(JB):		0.320
Kurtosis:	3.639	Cond	. No.		975.

Plot for Linear Model Coefficients for Our Model:



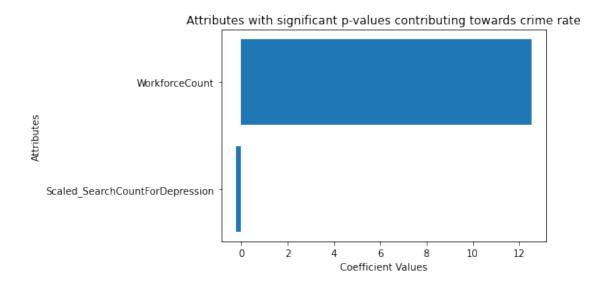
Our Model without ground truth: Linear Model summary:

		=====			=======	
Dep. Variable: Model:	<del>-</del>	unt OLS	-			0.160 0.133
Method:						6.042
	Least Squa				-).	
Date:	Sun, 11 Dec 2				c):	0.000175
Time:			_	Likelihood:		45.280
No. Observations:			AIC:			-80.56
Df Residuals:			BIC:			-66.15
Df Model:		4				
Covariance Type:	nonrob	ust				
=======================================	=========	=====			=======	
=======================================	:					
		(	coef	std err	t	P> t
[0.025 0.975]						
const		0.7	7992	0.456	1.752	0.082
-0.104 1.702						
WorkforceCount		12.5	5342	5.315	2.358	0.020
2.017 23.051						
PercentNegativeUser	s	-0.4	1293	0.237	-1.813	0.072
-0.898 0.039						
FavorOfDemocrats		-1.1	1609	0.876	-1.325	0.188
-2.895 0.573						
Scaled_SearchCountF	orDepression	-0.2	2289	0.087	-2.637	0.009
-0.401 -0.057	•					

			=======
Omnibus:	5.261	Durbin-Watson:	0.360
Prob(Omnibus):	0.072	Jarque-Bera (JB):	4.935
Skew:	0.358	Prob(JB):	0.0848
Kurtosis:	3.621	Cond. No.	457.

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

Plot for Linear Model Coefficients for Our Model without ground truth:



Till Dec-2021

#### Ground Truth:

Linear Model summary:

OLS Regression Results

Dep. Variable:	Scaled_CrimeCount	R-squared:	0.552
Model:	OLS	Adj. R-squared:	0.542
Method:	Least Squares	F-statistic:	52.67
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	3.06e-22
Time:	16:45:32	Log-Likelihood:	86.845
No. Observations:	132	AIC:	-165.7
Df Residuals:	128	BIC:	-154.2

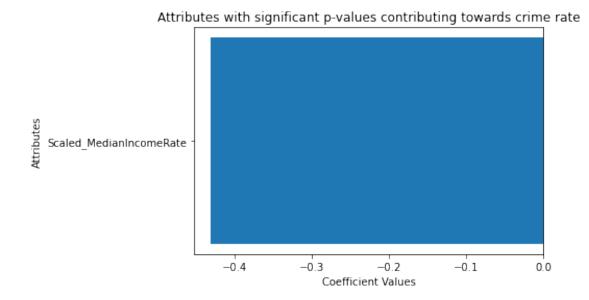
Df Model: 3
Covariance Type: nonrobust

	=========		========	========	
0.975]	coef	std err	t	P> t	[0.025
const	-3.8825	2.635	-1.473	0.143	-9.097
1.332					
Gender_ratio	8.4422	5.083	1.661	0.099	-1.615
18.499					
Scaled_Unemployment	0.0708	0.058	1.219	0.225	-0.044
0.186					
Scaled_MedianIncomeRate	-0.4305	0.049	-8.788	0.000	-0.527
-0.334					
Omnibus:	6.143	 	======================================	=======	0.555
Prob(Omnibus):	0.046	Jarque-	Bera (JB):		7.404
Skew:	0.274	Prob(JB			0.0247
Kurtosis:	4.023	Cond. N			635.
	========				=======

#### Notes:

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

Plot for Linear Model Coefficients for Ground Truth:



Our Model:

Linear Model summary:

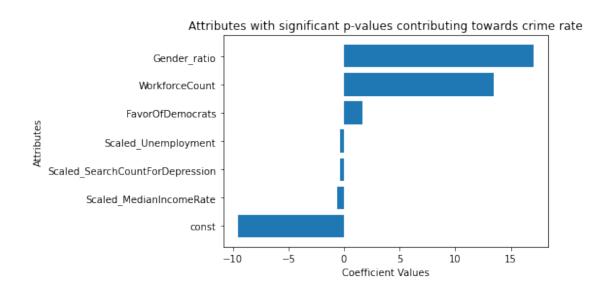
# OLS Regression Results

============		=====		.=======	========		
Dep. Variable:	Scaled_CrimeCount	R-squared: 0.799					
Model:	OLS		0.787				
Method:	Least Squares	t Squares F-statistic:					
Date:	Sun, 11 Dec 2022	Prob	o (F-statisti	ic):	3.94e-40		
Time:	16:45:32	Log-	-Likelihood:		139.56		
No. Observations:	132	AIC	:		-263.1		
Df Residuals:	124	BIC	:		-240.1		
Df Model:	7						
Covariance Type:	nonrobust						
		=====		=======	========		
		coef	std err	t	P> t		
[0.025 0.975]		COGI	Stu ell	C	17   0		
const	-9.	5504	1.861	-5.133	0.000		
-13.233 -5.868							
Gender_ratio	17.	0663	3.548	4.811	0.000		
10.045 24.088							
Scaled_Unemployment	-0.	3287	0.059	-5.598	0.000		
-0.445 -0.212	_						
Scaled_MedianIncomeR	ate -0.	6004	0.040	-15.035	0.000		
-0.679 -0.521	4.0	4500	0.074	5 000	0.000		
WorkforceCount	13.	4592	2.671	5.039	0.000		
8.173 18.745	0	1202	0 101	4 4 4 4	0.055		
PercentNegativeUsers -0.101 0.378	0.	1383	0.121	1.144	0.255		
	4	CCOE	0.538	3.091	0.002		
FavorOfDemocrats 0.598 2.729	1.	6635	0.556	3.091	0.002		
Scaled_SearchCountFo	rDepression -0.	3606	0.044	-8.159	0.000		
-0.448 -0.273	Thebression -0.	3000	0.044	-0.159	0.000		
=======================================		=====		.=======			
Omnibus:	6.452	Dur	oin-Watson:		1.211		
<pre>Prob(Omnibus):</pre>	0.040	Jaro	que-Bera (JB)	):	7.442		
Skew:	-0.315	Prob	o(JB):		0.0242		
Kurtosis:	3.978	Cond	d. No.		789.		
===============		=====		.=======			

### Notes:

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

#### Plot for Linear Model Coefficients for Our Model:



Our Model without ground truth: Linear Model summary:

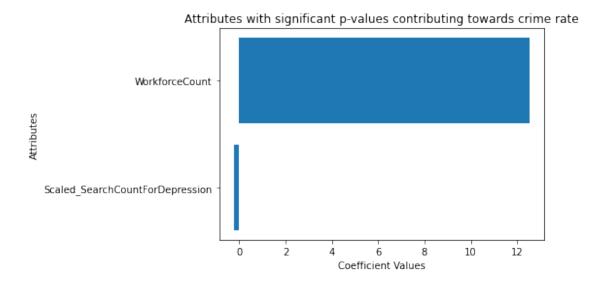
OLS Regression Results

		======		=======	========
Dep. Variable:	Scaled_CrimeCount	R-squa	ared:		0.160
Model:	OLS	Adj. F	R-squared:		0.133
Method:	Least Squares	F-stat	cistic:		6.042
Date:	Sun, 11 Dec 2022	Prob (	(F-statistic	:):	0.000175
Time:	16:45:32	Log-Li	kelihood:		45.280
No. Observations:	132	AIC:			-80.56
Df Residuals:	127	BIC:			-66.15
Df Model:	4				
Covariance Type:	nonrobust				
=======================================	=======================================	======			=========
=======================================					
		coef	std err	t	P> t
[0.025 0.975]					
const	0.	7992	0.456	1.752	0.082
-0.104 1.702					
WorkforceCount	12.	5342	5.315	2.358	0.020
2.017 23.051					
PercentNegativeUser	s -0.	4293	0.237	-1.813	0.072
-0.898 0.039					
· ·					

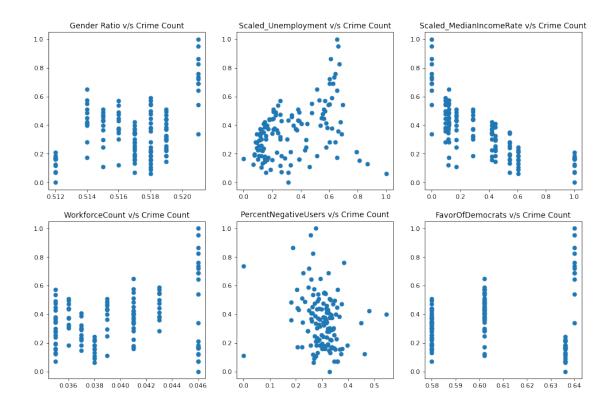
FavorOfDemocrats		-1.1609		0.876	-1.325	0.188
-2.895	0.573					
Scaled_SearchCountForDepression		-0.2289		0.087	-2.637	0.009
-0.401 -	0.057					
	=======================================		======	=======		=======
Omnibus:		5.261	Durbin-	Watson:		0.360
Prob(Omnibus)	:	0.072	Jarque-	Bera (JB):		4.935
Skew:		0.358	Prob(JB	):		0.0848
Kurtosis:		3.621	Cond. N	ο.		457.
						=======

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

Plot for Linear Model Coefficients for Our Model without ground truth:



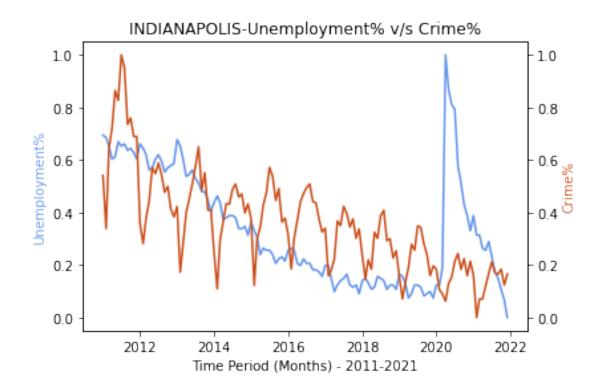
# Correlation Graphs:



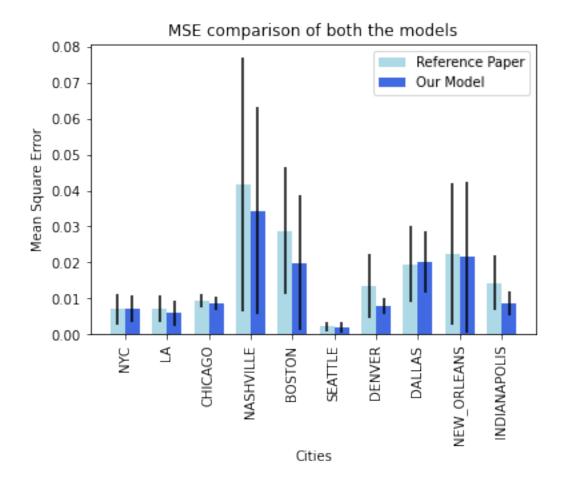
/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "g-" (-> color='g'). The keyword argument will take precedence.
 ax1.plot(city\_data["MonthYear"], city\_data['Scaled\_Unemployment'], 'g-',
color="#6495ED")

/var/folders/j\_/kdgw7x6d25j6yr\_1c3mwp9m40000gn/T/ipykernel\_39508/1320670805.py:1
2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b-" (-> color='b'). The keyword argument will take precedence.
 ax2.plot(city\_data["MonthYear"], city\_data['Scaled\_CrimeCount'], 'b-',
color="#CC4F1B")

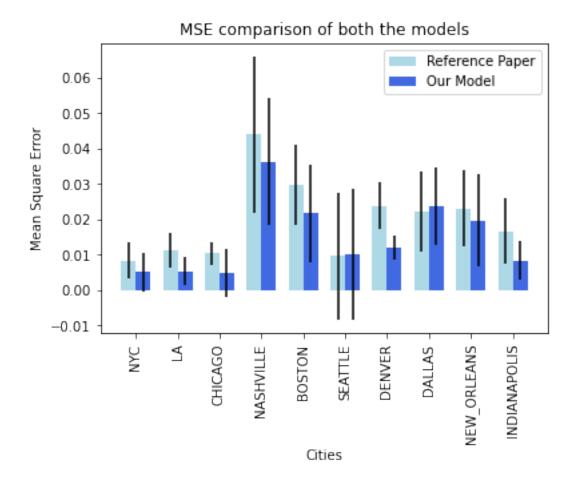
<Figure size 2400x1200 with 0 Axes>



Before Covid (Mar-2020)



Till Dec-2021



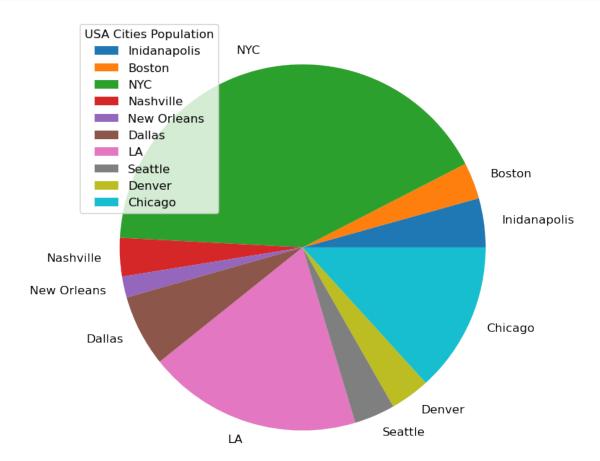
```
[25]: # USA Cities Population Pie Chart - Cities chosen for analysis for this project

USA = 331900000

total = 882039 + 654776 + 8468000 + 692587 + 376971 + 1288000 + 3849000 + 4733919 + 711463 + 2697000

def get_pop_perc(pop):
    # return round(float(pop / USA) * 100, 2)
    return pop/total

inidanapolis = get_pop_perc(882039)
boston = get_pop_perc(654776)
nyc = get_pop_perc(8468000)
nashville = get_pop_perc(692587)
new_orleans = get_pop_perc(376971)
dallas = get_pop_perc(1288000)
la = get_pop_perc(3849000)
```



```
[26]: # Playing around with FamaMacBeth Algo, with Newey-West adjustment
      # import pandas as pd
      # from linearmodels import FamaMacBeth # import package
      # ## 'panel' is a multi-index Pandas panel dataframe (stock code - date)
      # panel = pd.read_csv('~/Downloads/Sample.csv')
      # panel['date'] = pd.to_datetime(panel['Time'], format="\%b-\%y") # date should_\square
       ⇒be `datetime` format
      # panel = panel.set_index(['City', 'date']) # multi-index
      # print(panel)
      # mod = FamaMacBeth.from formula('Output ~ 1 + Input1 + Input2 + Input3',
       \rightarrow data=panel)
      # ## `bandwidth` is the lagged number of Newey-West, normally, bandwidth = 4(T/
       →100) ^ (2/9)
      # ## Remove all Settings in parentheses if newey-West adjustments are not !!
      # res = mod.fit(cov_type= 'kernel', debiased = False, bandwidth = 3)
      # print(res.summary)
[27]: # Barebone implementation of FamaMacBeth
      # def ols_coef(x, formula):
          return smf.ols(formula,data=x).fit().params
      # panel = pd.read_csv('~/Downloads/Sample.csv')
      # panel['date'] = pd.to_datetime(panel['Time'], format="%b-%y")
      # gamma = (panel.groupby('date').apply(ols_coef,'Output ~ 1 + Input1 + Input2 +
       →Input3'))
      # print(qamma.head())
      # def fm_summary(p):
           s = p.describe().T
            s['std_error'] = s['std']/np.sqrt(s['count'])
            s['tstat'] = s['mean']/s['std error']
            return s[['mean', 'std_error', 'tstat']]
      # print(fm_summary(gamma))
[28]: # Chicago Covid Comparison
      # chicago_covid = pd.read_csv('~/Documents/Practice/Chicago_Covid.csv',_
      ⇔header=None)
      # chicago covid.columns = ['Perc', 'MonthYear']
      # chicago_covid['MonthYear'] = pd.to_datetime(chicago_covid['MonthYear'],_
       \hookrightarrow format="%b-%Y")
      # chicago_covid = chicago_covid.sort_values(by=['MonthYear'])
```

```
# chicago_dataset = pd.read_csv('~/Documents/Practice/
→chicago_city_final_dataset_v2.csv')
# chicago_dataset['MonthYear'] = pd.to_datetime(chicago_dataset['MonthYear'],u
\rightarrow format = "\%b - \%y")
# chicago combined dataset covid = chicago dataset[chicago dataset['MonthYear']_
→>= '2020-03-01'7
# perc = []
# for index, row in chicago_combined_dataset_covid.iterrows():
     month_year = row['MonthYear']
     perc_pos_covid_cases = chicago_covid[chicago_covid['MonthYear'] ==__
 →month_year]['Perc']
     perc.append(float(perc_pos_covid_cases))
# chicago combined dataset covid['CovidPercPositive'] = perc
# regress_our_model_for_covid(chicago_combined_dataset_covid, 2)
# regress_our_model(chicago_combined_dataset_covid, 2)
```

```
[29]: | # Trying out OLS Regression with multivariate implementation
      # import statsmodels.api as sm
      # city_data = pd.read_csv('~/Documents/Practice/CSV_LA_city_final_dataset_v2.
      ⇔csv')
      # normalize_dataset(city_data)
      # y = city_data['Scaled_CrimeCount']
      # x = city_data.loc[:,['Gender_ratio', 'Scaled_Unemployment',_
       → 'Scaled_MedianIncomeRate']]
      \# X = sm.add constant(x)
      # lin_model = sm.OLS(y, X)
      # regr_results = lin_model.fit()
      # print(regr results.summary())
      # print(list(regr_results.params))
      # transformer = PolynomialFeatures(degree=6, include_bias=False)
      \# x_{-} = transformer.fit_transform(x)
      \# x_{-} = pd.DataFrame(np.array(x_{-}), columns=transformer.get_feature_names_out())
      \# X = sm.add\_constant(x_{-})
      \# poly_model = sm.OLS(y, X)
      # reqr_results = poly_model.fit()
      # print(reqr_results.summary())
```

```
[30]: # Playing around with the interaction terms
             # city_data = pd.read csv("~/Documents/Practice/chicago_city_final_dataset_v2.
              ⇒csv".format(absolute_file_path, city_file), header=0)
             # city data = add mental health data("CHICAGO", city data, "~/Documents/
              →Practice")
             # y = city_data['Cul. Crime count']
             \# x = city \ data.loc[:,['Gender \ ratio', 'UnemploymentRate', 'MedianIncomeRate', \sqcup
              → 'WorkforceCount', 'PercentNegativeUsers', 'FavorOfDemocrats', □
              → 'SearchCountForDepression']]
             # transformer = PolynomialFeatures(degree=2, include_bias=False)
             \# x = transformer.fit transform(x)
             # z = transformer.get_feature_names_out()
            # # for idx, ele in enumerate(z):
                          if idx in [3, 7, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 22, 23, 24, ]
              →25, 28, 30, 31]:
            # #
                                     print("{}: {}".format(idx, ele))
             # # print(remove_interaction_terms(z, [19, 26, 33, 34]))
            # # print(list(z[:10]) + list(z[11:19]) + list(z[20:31]) + list(z[32:]))
            \# \# print(z[:7] + [z[12]] + [z[17]] + [z[21]] + [z[24]] + [z[26]])
             # # Removing interaction terms
            \# new x = []
            # interaction_terms = [1, 8, 14, 17, 19, 22, 24, 26, 28, 29, 30, 31, 33]
             # for item in x:
             # #
                            temp = list(item[:5]) + list(item[6:10]) + list(item[11:19]) + list(item[:5]) + list(item
               →list(item[20:22]) + list(item[23:25]) + list(item[28:31]) + list(item[32:])
                         temp = remove_interaction_terms(item, interaction_terms)
                         new x .append(temp)
             #### new x = pd.DataFrame(np.array(new x), columns=list(z[:5]) + list(z[6:
              (-10]) + list(z[11:19]) + list(z[20:22]) + list(z[23:25]) + list(z[28:31]) + (-10]
              \hookrightarrow list(z[32:]))
             # new_x_ = pd.DataFrame(np.array(new_x_), columns=remove_interaction_terms(z, line))
              →interaction_terms))
             # # new_x = pd.DataFrame(np.array(x_), columns=z)
             \# X = sm.add constant(new x)
             # regr_results = sm.OLS(list(y), X).fit()
            # regr_results.summary()
[31]: # 0: Gender ratio
            # 1: UnemploymentRate
            # 2: MedianIncomeRate
```

# 3: WorkforceCount

```
# 4: PercentNegativeUsers
# 5: FavorOfDemocrats
# 6: SearchCountForDepression
# 7: Gender_ratio^2
# 8: Gender_ratio UnemploymentRate
# 9: Gender_ratio MedianIncomeRate
# 10: Gender ratio WorkforceCount
# 11: Gender_ratio PercentNegativeUsers
# 12: Gender ratio FavorOfDemocrats
# 13: Gender_ratio SearchCountForDepression
# 14: UnemploymentRate^2
# 15: UnemploymentRate MedianIncomeRate
# 16: UnemploymentRate WorkforceCount
# 17: UnemploymentRate PercentNegativeUsers
# 18: UnemploymentRate FavorOfDemocrats
# 19: UnemploymentRate SearchCountForDepression
# 20: MedianIncomeRate 2
# 21: MedianIncomeRate WorkforceCount
# 22: MedianIncomeRate PercentNegativeUsers
# 23: MedianIncomeRate FavorOfDemocrats
# 24: MedianIncomeRate SearchCountForDepression
# 25: WorkforceCount^2
# 26: WorkforceCount PercentNegativeUsers
# 27: WorkforceCount FavorOfDemocrats
# 28: WorkforceCount SearchCountForDepression
# 29: PercentNegativeUsers~2
# 30: PercentNegativeUsers FavorOfDemocrats
# 31: PercentNegativeUsers SearchCountForDepression
# 32: FavorOfDemocrats^2
# 33: FavorOfDemocrats SearchCountForDepression
# 34: SearchCountForDepression^2
```