Spillover Effects of Mass Shootings

In this notebook we study the effects of mass shootings on tangential "shooting" related economies, in particular counter strike.

The main question being "**does demand for shooting activities increase after a mass shooting**?"

Mass shootings are a relatively new phenomenon throughout human history, with increasing frequency. Few things are known about mass shootings in economies, namely demand for firearms and security increase but overall business decreases. This project focuses on mass shootings effects on tangential “shooting” related economies. One example would be first person shooting (FPS) games. Would mass shootings serve as a marketing tool or a deterrence to FPS games. We hypothesize that after a mass shooting, demand for related activities will increase, dependent on the amount of physical human.

To analyze this question, we first use interactive maps to show the basic pattern of Mass Shooting severity and the Counter Strike popularity in each state. Then we use some linear regressions to investigate the relationship. Finally we conduct dynamic DID and conclude that relatively “small” Mass Shootings increase the CS popularity while relatively “large” Mass Shootings reduce the CS popularity.

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import matplotlib.dates as mdates
from sklearn import (linear_model, metrics, neural_network, pipeline, model_selection)
import seaborn as sns
import geopandas as gpd
from bokeh.plotting import figure, ColumnDataSource
from bokeh.io import output_notebook, show, output_file
from bokeh.models import GeoJSONDataSource, LinearColorMapper, ColorBar, HoverTool
from bokeh.palettes import brewer
import json
import csv
from shapely.geometry import Point
from datetime import timedelta,datetime
from pandas.tseries.offsets import DateOffset
from linearmodels.panel import PanelOLS
import statsmodels.formula.api as smf
import statsmodels.api as sm
from statsmodels.iolib.summary2 import summary_col
%matplotlib inline
```

1 Collect and explore the data

1.1 Data collection

To explore the relationship between mass shooting and counter strike popularity, we use the data below, which is mainly from Mother Jones'Investigation and Google Trends:

- **Mass shooting data**
  - all the events: Mother Jones - Mass Shootings Database, 1982 - 2023 - Sheet1.csv
- **Counter Strike popularity data**
  - by state: CS_State_Map.xlsx
  - by month: Counter Strike.csv
  - by state and month: CS_panel data.csv
- **Other popularity data**
  - Airsoft popularity: airsoft map.csv
  - Laser Tag popularity: laser tag map.csv
- **Control variables**
  - income information: Income per county.csv

In [ ]:
```
url1 = "Mother Jones - Mass Shootings Database, 1982 - 2023 - Sheet1.csv"
url2 = "Income per county.csv"
url3 = "CS_State_Map.xlsx"
url4 = "Counter Strike.csv"
url5 = "CS_panel data.csv"
url6 = "airsoft map.csv"
url7 = "laser tag map.csv"

# load raw data
shootings = pd.read_csv(url1, encoding='iso-8859-1', parse_dates=["date"])
income = pd.read_csv(url2, encoding='latin-1')
CS = pd.read_excel(url3)
CS_month = pd.read_csv(url4, encoding='iso-8859-1', parse_dates=["Month"])
original_panel_data = pd.read_csv(url5,  parse_dates=["Month"])
airsoft = pd.read_csv(url6, encoding='iso-8859-1')
laser = pd.read_csv(url7, encoding='iso-8859-1')

# data cleaning
# melt the short data frame to long data frame
panel_data = pd.melt(original_panel_data, id_vars='Month', var_name='state', value_name='CS popularity')
panel_data['Month'] = pd.to_datetime(panel_data['Month'], format='%Y-%m-%d')
# get the state information
shootings1 = pd.concat([shootings, shootings["location"].str.split(', ', expand=True)], axis=1).rename(columns=
MS=shootings1[["date","Region","fatalities"]]
# get the recent Mass Shootings
MS_events=shootings1[["Region","date","fatalities"]]
MS_events=MS_events[(MS_events["date"]>='2010-01-01') & (MS_events["date"]<='2023-07-01')]
#clean the data for regression 1
def cleandata_regression1(dataset,valname,rename):
    final = pd.merge(shootings1, dataset, on="Region").filter(['case','City','Region' ,valname, 'year'], axis=1
    final["MS"] = final.groupby('Region')['Region'].transform('count')
    X=final.drop(["case", "City", "year"], axis=1).copy()
    X=X.drop_duplicates()
    X[rename]=X[valname]
    return X
X=cleandata_regression1(CS, 'Counter Strike: (1/1/04 - 3/28/23)','CS')
```

1.2 Data exploration

In this step, we explore the data to gain insights and identify trends and patterns of mass shooting and counter strike popularity using visualizations such as maps, a scatter plot and line graphs.

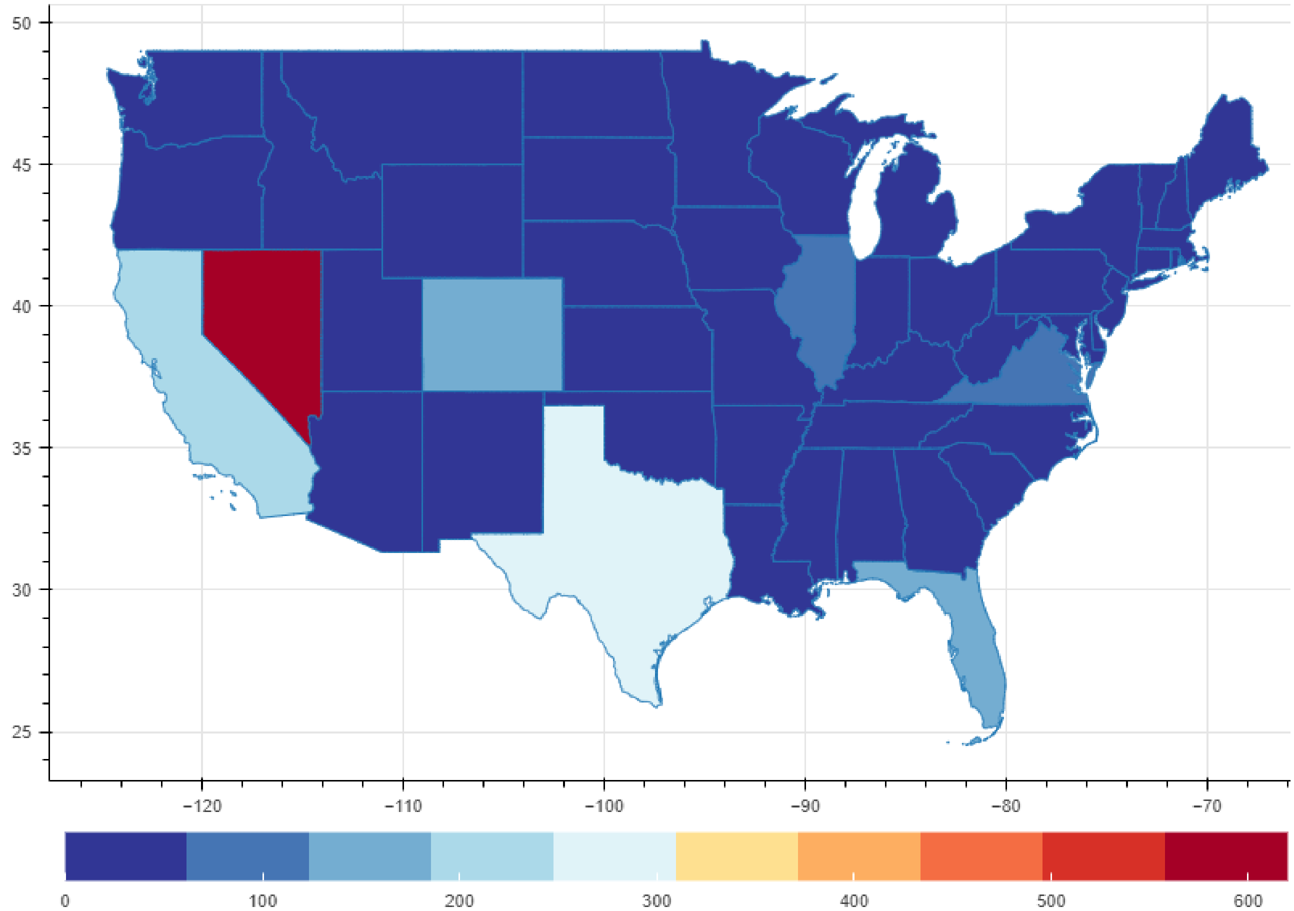
1.2.1 Interactive maps for Mass Shooting victim number and Counter Strike popularity

In [ ]:
```
states = gpd.read_file('https://www2.census.gov/geo/tiger/GENZ2019/shp/cb_2019_us_state_500k.zip')
states_df = gpd.read_file("https://datascience.quantecon.org/assets/data/cb_2016_us_state_5m.zip")
states_df = states_df.query("NAME != 'United States Virgin Islands'")
```

```
states_df = states_df.query("NAME != 'Commonwealth of the Northern Mariana Islands'")
states_df = states_df.query("NAME != 'Alaska'")
states_df = states_df.query("NAME != 'Hawaii'")
state_counts = {}

with open('Mother Jones - Mass Shootings Database, 1982 - 2023 - Sheet1.csv', 'r', encoding='utf-8') as file:
    shootings_reader = csv.reader(file)
    next(shootings_reader)
    for row in shootings_reader:
        state = row[1].split(',')[1].strip()
        if state == "D.C.":
            state = "District of Columbia"
        if not row[6].isdigit():
            row[6] = row[4]
        try:
            date = datetime.strptime(row[2], "%m/%d/%y")
        except ValueError:
            date = datetime.strptime(row[2], "%m/%d/%Y")
        if date >= datetime(2004, 1, 1):
            count = int(row[6])
            state_counts[state] = state_counts.get(state, 0) + count
missing_states = ['New Hampshire', 'Rhode Island', 'Maine', 'Vermont',
                  'South Dakota', 'Wyoming', 'North Dakota', 'West Virginia',
                  'Montana', 'New Mexico', 'Delaware','Idaho','Louisiana','Utah', 'Arizona', 'Nebraska','Iowa',
                  'Minnesota', 'Kentucky', 'Arkansas', 'Mississippi', 'Massachusetts', 'Connecticut', 'Illinois
for state in missing_states:
    if state not in state_counts:
        state_counts[state] = 0
df_state_counts = pd.DataFrame({'State': list(state_counts.keys()), 'Count': list(state_counts.values())})
mass_states = states_df.merge(df_state_counts, left_on="NAME",  right_on="State", how="inner")
output_notebook()
states_geojson=GeoJSONDataSource(geojson=mass_states.to_json())
color_mapper = LinearColorMapper(palette = brewer['RdYlBu'][10], low = 0, high = 620)
color_bar = ColorBar(color_mapper=color_mapper, label_standoff=8,width = 760, height = 30,
                     border_line_color=None,location = (0,0), orientation = 'horizontal')
hover = HoverTool(tooltips = [ ('State','@State'),('Total Victims', '@Count')])

p = figure(title="Figure 1. Mass Shootings by Total Victims, 2004 - 2023", tools=[hover], plot_width=850, plot_
p.patches("xs","ys",source=states_geojson,
          fill_color = {'field' :'Count', 'transform' : color_mapper})
p.add_layout(color_bar, 'below')
show(p)
```

Loading BokehJS ...

Figure 1. Mass Shootings by Total Victims, 2004 - 2023



This choropleth map shows the total numbers of victims of mass shootings in each US state from 2004 to 2023. The redder the color of the state, the higher the numbers of victims.

From the map, we can see that some states stand out as having a higher number of mass shooting victims, such as Nevada(616), Texas(262), California(223),Florida(175) and Colorado(140). Other states, such as New Mexico(0), Mississippi(0) and Iowa(0), have relatively few mass shooting victims. We notice that the victim number for most of the states is below 100.

The map is interactive, allowing us to hover over each state and see its name and the total number of victims. This feature can be useful for identifying specific states with high numbers of victims and for comparing the relative number of victims between states.

Overall, this choropleth map provides a clear visualization of the distribution of mass shooting victims across the US.

In [ ]:
```
counter_strike = CS.rename({'Counter Strike: (1/1/04 - 3/28/23)':'cs_popularity'}, axis=1)
cs_w_states = states_df.merge(counter_strike, left_on="NAME",  right_on="Region", how="inner")
output_notebook()
cs_states_geojson=GeoJSONDataSource(geojson=cs_w_states.to_json())
color_mapper = LinearColorMapper(palette = brewer['RdYlBu'][10], low = 0, high = 100)
color_bar = ColorBar(color_mapper=color_mapper, label_standoff=8,width = 780, height = 30,
                     border_line_color=None,location = (0,0), orientation = 'horizontal')
hover = HoverTool(tooltips = [ ('State','@NAME'),('CS popularity', '@cs_popularity')])
p = figure(title="Figure 2. Counter Strike Popularity Map, 2004 - 2023", tools=[hover], plot_width=850, plot_he
p.patches("xs","ys",source=cs_states_geojson,
          fill_color = {'field' :'cs_popularity', 'transform' : color_mapper})
p.add_layout(color_bar, 'below')
show(p)
```

BokehJS 2.4.2 successfully loaded.

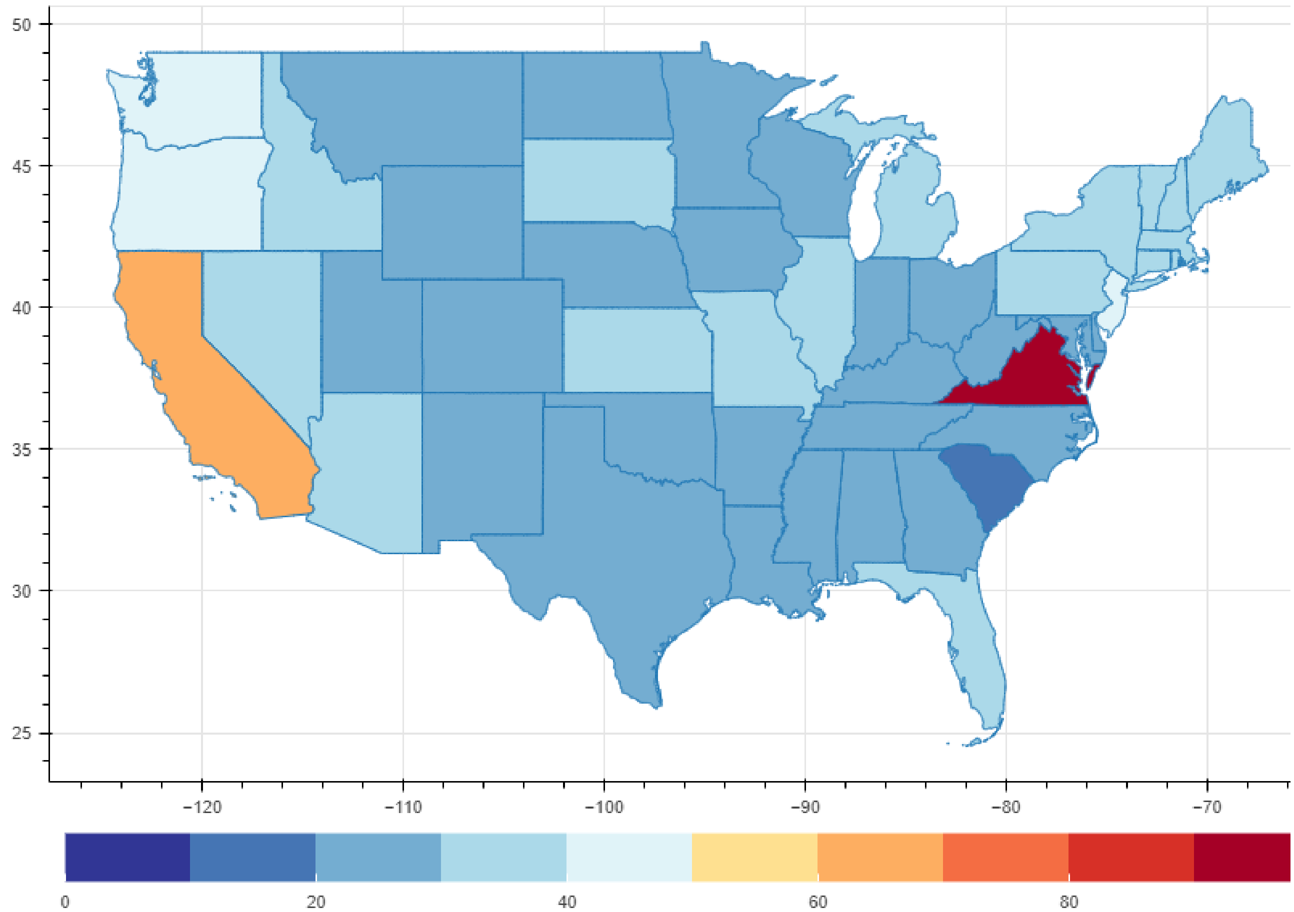


Figure 2. Counter Strike Popularity Map, 2004 - 2023

The second plot shows a map of the United States with each state colored according to its level of popularity for the game Counter Strike (CS) from 2004 to 2023. The redder the color of the state, the higher the CS popularity in that state. Similar to the first plot, the states are outlined and labeled with their names. From the above interactive map of Counter Strike popularity from 2004 to 2023, we notice that CS popularity for most of the states is around 30.

However, it is high for states in the western coast and northeastern coast, especially for Virginia(100) and California(64).

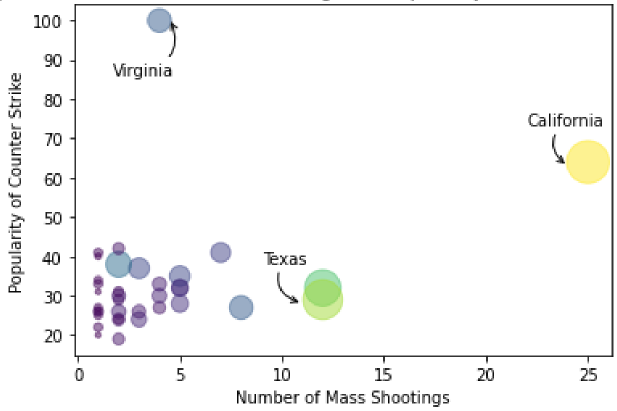
Comparing the two maps above, we observe that: **states with high victim number** partly match with **states with high CS popularity**.We can see that there seem to be a relationship between the CS popularity and the number of victims from mass shootings.

1.2.2 scatter plot: Mass Shootings and CS popularity

In [ ]:

```
scatter=pd.merge(MS.groupby("Region").sum(),X, on="Region")
fig, ax = plt.subplots()
ax.scatter(scatter["MS"],scatter["CS"], s=scatter["fatalities"]*4, c=scatter["fatalities"], alpha=0.5)
ax.set_xlabel("Number of Mass Shootings")
ax.set_ylabel("Popularity of Counter Strike")
ax.set_title("Figure 3. Scatter Plot: Mass Shootings, CS Popularity and Fatalities by State")

for i, row in scatter[(scatter['Region']=='California') | (scatter['Region']=='Texas')].iterrows():
    ax.annotate(row['Region'], (row['MS']-1, row['CS']-1),xytext=(-25, 25), textcoords="offset points",
    arrowprops=dict(arrowstyle="->", connectionstyle="arc3,rad=0.6"))
for i, row in scatter[(scatter['Region']=='Virginia') ].iterrows():
    ax.annotate(row['Region'], (row['MS']+0.5, row['CS']+0.5), xytext=(-35, -35), textcoords="offset points",
    arrowprops=dict(arrowstyle="->", connectionstyle="arc3,rad=0.6"))
plt.show()
```

Figure 3. Scatter Plot: Mass Shootings, CS Popularity and Fatalities by State



This scatter plot shows the relationship between the number of mass shootings (MS) and the popularity of Counter Strike (CS) in different states. Each point in the plot represents a state, and the size of the point indicates the number of fatalities resulting from mass shootings in that region.

From the scatter plot, we can see that there is a linear relationship between mass shootings and CS popularity. The scatter plot also includes labels for three states: California, Texas, and Virginia, allowing us to easily identify the states with the highest and lowest MS counts and CS popularity.

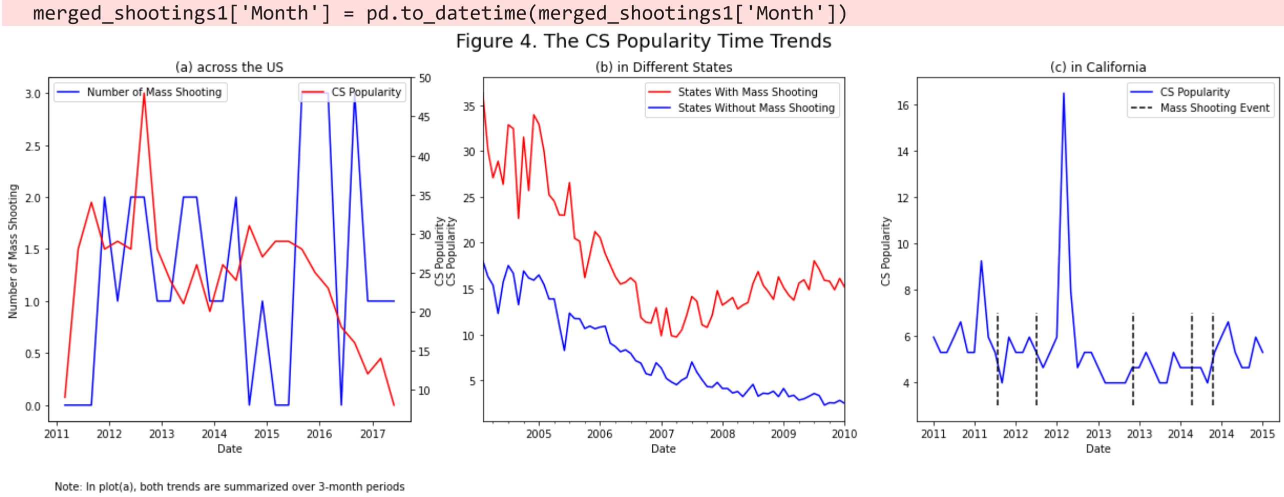
Overall, the scatter plot shows that there is a positive relationship between the popularity of Counter Strike and the number of mass shootings in each state. This is evident from the general upward trend of the dots as we move from left to right in the plot. The plot also shows that the number of fatalities in each state varies greatly, with some states having a higher number of fatalities than others.

1.2.3 line graphs: time trends of Mass Shooting event number and CS popularity

In [ ]:
```
fig, ax = plt.subplots(1,3,figsize=(21, 6))
fig.suptitle('Figure 4. The CS Popularity Time Trends',fontsize=18)
# the first line graph
monthly_shootings = shootings.groupby(pd.Grouper(key='date', freq='M')).count()
monthly_shootings = monthly_shootings.reset_index()
monthly_shootings = monthly_shootings[['date', 'case']]
monthly_shootings = monthly_shootings.rename(columns={'date': 'Month', 'case': 'Number of Incidents'})
monthly_shootings['Month']=monthly_shootings['Month'] + timedelta(days=1) - DateOffset(months=1)
monthly_shootings['Month'] = pd.to_datetime(monthly_shootings['Month'], format='%Y-%m-%d')
CS_month['Month'] = pd.to_datetime(CS_month['Month'], format='%b-%y')
merged_shootings = pd.merge(monthly_shootings, CS_month, on='Month')
merged_shootings1 = merged_shootings.loc[(merged_shootings['Month'] >= '2011-02-01') &  (merged_shootings['Mont
merged_shootings1['Month'] = pd.to_datetime(merged_shootings1['Month'])
merged_shootings1.set_index('Month', inplace=True)
merged_shootings2 = merged_shootings1.resample('3M').sum()
merged_shootings2=merged_shootings2.reset_index()
ax[0].plot(merged_shootings2['Month'], merged_shootings2['Number of Incidents'], color='blue', label='Number of
ax[0].set_ylabel('Number of Mass Shooting')
ax2 = ax[0].twinx()
ax2.plot(merged_shootings2['Month'], merged_shootings2['counter strike: (United States)'], color='red', label='
ax2.set_ylabel('CS Popularity')
ax[0].legend(loc='upper left')
ax2.legend(loc='upper right')
ax[0].set_xlabel('Date')
ax[0].set_title('(a) across the US')
plt.annotate('Note: In plot(a), both trends are summarized over 3-month periods', xy=(0.5, -0.2), xycoords='axe

# the second line graph
A=MS_events.groupby("Region")
shootings_data=MS_events.loc[A["fatalities"].idxmax()]
shootings_data=shootings_data[shootings_data["fatalities"]>=10]
merged_data = pd.merge(panel_data, shootings_data, how='left', left_on=['state'],right_on=['Region'])
merged_data['treatment'] = np.where(merged_data['date'].notnull(), 1, 0)  # define treatment group and control
merged_data = merged_data.rename(columns={'CS popularity': 'CS_popularity'})
plot_trends=merged_data[merged_data['Month']<='2010-01-01']
plot_trends.query('treatment == 1').groupby('Month')['CS_popularity'].mean().\
plot(ax=ax[1], color='red', label='States With Mass Shooting')# treatment group
```

```
plot_trends.query('treatment == 0').groupby('Month')['CS_popularity'].mean().\
plot(ax=ax[1], color='blue', label='States Without Mass Shooting')# control group
ax[1].set_xlabel('Date')
ax[1].set_ylabel('CS Popularity')
ax[1].set_title('(b) in Different States')
ax[1].legend()

# the third line graph
California_MS=shootings1[shootings1["Region"]=='California']['date']
California_MS=California_MS[(California_MS>='2011-01-01') & (California_MS<='2015-01-01')]
California_CS=merged_data[merged_data["state"]=='California']
California_CS=California_CS[(California_CS["Month"]>='2011-01-01') & (California_CS["Month"]<='2015-01-01')]
ax[2].plot(California_CS['Month'],
        California_CS['CS_popularity'], color='blue')
lines = []
for x in list(California_MS):
    line = ax[2].vlines(x, 3, 7, colors='black', linestyles='dashed')
    lines.append(line)
ax[2].legend([ax[2].lines[0], lines[1]], ['CS Popularity', 'Mass Shooting Event'])
ax[2].set_xlabel('Date')
ax[2].set_ylabel('CS Popularity')
ax[2].xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:.0f}'.format(mdates.num2date(x).year)))
ax[2].set_title('(c) in California')
plt.show()
```

```
C:\Users\lenovo\AppData\Local\Temp\ipykernel_5520\1023738929.py:13: 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#re
turning-a-view-versus-a-copy
  merged_shootings1['Month'] = pd.to_datetime(merged_shootings1['Month'])
```



This section presents three line graphs depicting the relationship between CS popularity and mass shootings across three distinct levels: a general level, a state level, and a specific event level.

- **Plot(a)** shows the trends of CS popularity and mass shooting numbers across the US. \ We notice that in general the rise of CS popularity(red) comes with the rise of Mass Shooting(blue) event number.
- **Plot (b)** shows the trends of CS popularity for states with mass shooting and states without mass shooting.\ Visually, we see states with mass shootings (red) seem to have a consistently higher counter strike popularity as compared to states without mass shootings (blue). And that gap continued to increase since 2007. This suggests that there is a correlation with mass shootings and counter strike popularity.
- **Plot(c)** shows the change of CS popularity after Mass Shooting events in California.\ The dates of mass shooting events in California are marked with dashed lines. We notice that CS popularity rises after each Mass Shooting event.

2 Preliminary data analysis

In this step, we identify correlations or relationships between variables.We conduct preliminary data analysis such as simple linear regression to assess the feasibility of examining the causality with the available data.

2.1 Simple linear regression

2.1.1 MS number and CS popularity

Firstly, we examine the correlation by

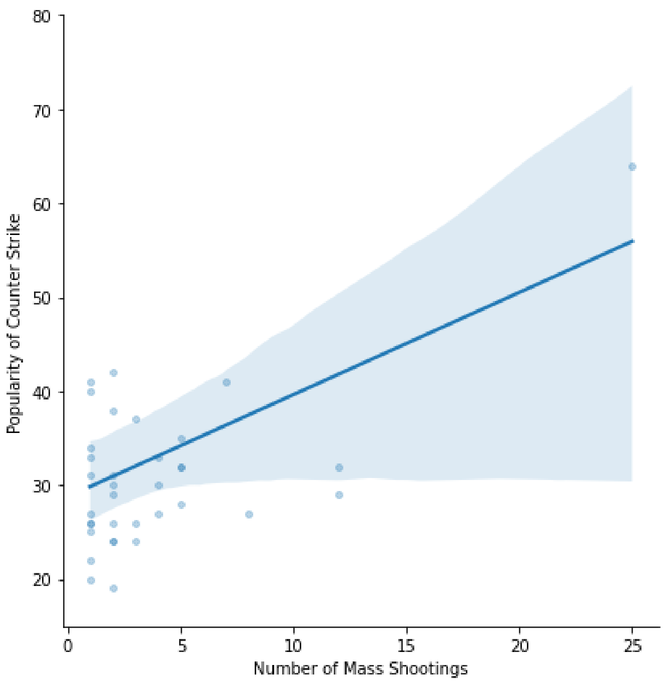
$$CS_i = \beta_0 + \beta_1 totalMS_i + \epsilon \qquad (1)$$

where:

- i denotes state;
- CS_i denotes the total Counter Strike popularity for state i;
- $totalMS_i$ denotes the total number of Mass Shooting events in state i;
- ϵ is the error term.

In [ ]:
```
g1=sns.lmplot(data=cleandata_regression1(CS,'Counter Strike: (1/1/04 - 3/28/23)','CS'), x="MS", y="CS", height=
    scatter_kws=dict(s=15, alpha=0.3))
g1.set_axis_labels("Number of Mass Shootings", "Popularity of Counter Strike")
plt.title('Figure 5. Linear Regresion: MS Number and CS Popularity',y=1.05,fontsize=14)
plt.ylim(15,80)
plt.show()
```

Figure 5. Linear Regresion: MS Number and CS Popularity



The code generates a scatterplot with a regression line depicting the relationship between the number of mass shootings and the popularity of Counter Strike across the US from January 1st, 2004 to March 28th, 2023. The scatterplot shows the distribution of the data points, where each point represents a specific combination of mass shooting number and Counter Strike popularity. The regression line represents the best fit line through the data points, indicating the direction and strength of the relationship between the two variables.

The results suggest that as the number of mass shootings increases, the popularity of Counter Strike also tends to increase.

In [ ]:
```
shootings_lr_model = linear_model.LinearRegression()
shootings_lr_model.fit(X[["MS"]], X["CS"])
beta_0 = shootings_lr_model.intercept_ # get the coefficients
beta_1 = shootings_lr_model.coef_[0]
model1 = smf.ols(formula='CS~ MS', data=X)
result = model1.fit(cov_type='HC3')
print(result.summary())
print(f"Counter Strike Popularity= {beta_0:.4f} + {beta_1:.4f} Number of Mass Shootings")
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                     CS   R-squared:                       0.125
Model:                            OLS   Adj. R-squared:                  0.100
Method:                 Least Squares   F-statistic:                     2.537
Date:                Mon, 24 Apr 2023   Prob (F-statistic):              0.120
Time:                        19:32:50   Log-Likelihood:                -143.37
No. Observations:                  36   AIC:                             290.7
Df Residuals:                      34   BIC:                             293.9
Df Model:                           1                                         
Covariance Type:                  HC3                                         
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     28.7469      2.943      9.766      0.000      22.978      34.516
MS             1.0878      0.683      1.593      0.111      -0.251       2.426
==============================================================================
Omnibus:                       60.269   Durbin-Watson:                   2.068
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              504.192
Skew:                           3.744   Prob(JB):                    3.28e-110
Kurtosis:                      19.735   Cond. No.                         7.86
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
Counter Strike Popularity= 28.7469 + 1.0878 Number of Mass Shootings
```

The regression equation is: Counter Strike Popularity = 28.7469 + 1.0878 Number of Mass Shootings.

The linear regression model shows that the number of mass shootings is positively and significantly associated with the popularity of Counter Strike (CS) video game (β= 1.0878, $p<0.2$). This means that for every one-unit increase in the number of mass shootings, the popularity of CS increases by an average of 1.0878 units.

2.1.2 MS number and popularity of airsoft and laser tag

To examine whether MS has a similar effect on other things such as airsoft and laser tag, we conduct the below regression which is similar to regression(1).

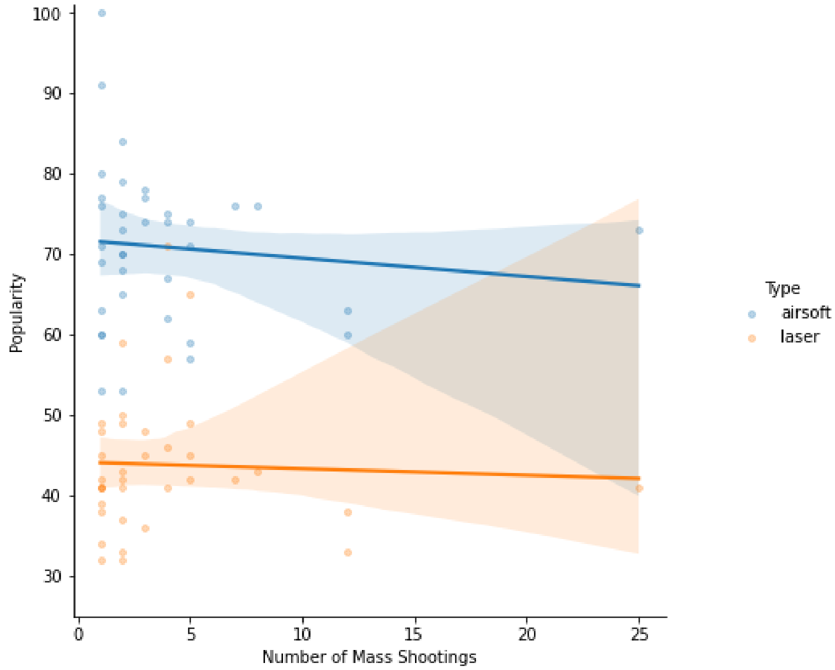
$$Y_i = \beta_0 + \beta_1 totalMS_i + \epsilon \qquad (2)$$

where Y_i denotes the total Airsoft or Laser Tag popularity for state i and other variables are the same as those in regression(1).

In [ ]:

```python
# data cleaning: merge 'airsoft' and 'laser' columns into one column 'value'
d1=cleandata_regression1(airsoft,'airsoft: (2004/1/1 - 2023/4/10)','airsoft')
d2=cleandata_regression1(laser,'laser tag: (2004/1/1 - 2023/4/10)','laser')
combined=pd.merge(d1,d2,on=["Region","MS"])
combine = pd.melt(combined, id_vars=['MS'], value_vars=['airsoft', 'laser'], var_name='Type', value_name='value

# create the lmplot
g2 = sns.lmplot(data=combine,
                x='MS', y='value', hue='Type', height=6,
                scatter_kws=dict(s=15, alpha=0.3))
g2.set_xlabels('Number of Mass Shootings')
g2.set_ylabels('Popularity')
plt.title('Figure 6. Linear Regresion: MS Number and the Popularity of Airsoft and Laser Tag',y=1.03,fontsize=1
plt.ylim(25,101)
plt.show()
```

Figure 6. Linear Regresion: MS Number and the Popularity of Airsoft and Laser Tag



The regression line slopes for both types are small and show no significant correlation between the number of mass shootings and the popularity of airsoft or laser tag.

Therefore, we will continue to use CS popularity data to examine the effect.

2.2 Linear regression: MS number and the change of CS popularity

Secondly, we examine the correlation by

$$\Delta CS_{it+1} = \beta_0 + \beta_1 MS_{it} + \epsilon \quad (3)$$
$$\Delta CS_{it+1} = \beta_0 + \beta_1 MS_{it} + \gamma_i + \epsilon \quad (4)$$
$$\Delta CS_{it+1} = \beta_0 + \beta_1 MS_{it} + \beta_2 Fat_{it} + \epsilon \quad (5)$$
$$\Delta CS_{it+1} = \beta_0 + \beta_1 MS_{it} + \beta_2 Fat_{it} + \gamma_i + \epsilon \quad (6)$$

where:

- i denotes state, t denotes the date,γ_i denotes state fixed effect;
- $\Delta CS_{it+1} = CS_{it+1} - CS_{it}$ denotes the Counter Strike popularity for state i in month t+1 minus the Counter Strike popularity for state i in month t, namely the change of Counter Strike popularity for state i;
- MS_{it} is a dummy variable, which equals 1 when there is at least 1 Mass Shooting events for state i in month t and equals 0 otherwise;
- Fat_{it} is the fatalities during Mass Shooting for state i in month t;
- ϵ is the error term.

Regression(5) and (6) take fatalities, namely the intensity of Mass Shooting into consideration.\ Regression(4) and (6) take state fixed effects into consideration.

In [ ]:
```
#cleaning data
MS['date'] = pd.to_datetime(MS['date']) # get the Mass Shooting date for each state
panel_data["CSdiff"]=panel_data["CS popularity"].shift(-1) - panel_data["CS popularity"] # generate the change
panel_data=panel_data[panel_data["Month"]!='2004-01-01']
merged = pd.merge(panel_data, MS, left_on='state',right_on='Region')
merged["time_diff"]=merged["Month"]-merged["date"]
merged["shooting"]=np.where(((merged['time_diff'].dt.days >= 0) & (merged['time_diff'].dt.days <= 30)) , 1, 0)
merged["fatality"]=merged["fatalities"]*merged["shooting"]# generate fatality number

#run regression
res_ols1 = smf.ols(formula='CSdiff~shooting', data=merged).fit(cov_type='HC3') #regression(2)
res_ols2 = smf.ols(formula='CSdiff~shooting+state', data=merged).fit(cov_type='HC3') #regression(3)
```

```
res_ols3 = smf.ols(formula='CSdiff~shooting+fatality', data=merged).fit(cov_type='HC3') #regression(4)
res_ols4 = smf.ols(formula='CSdiff~shooting+fatality+state', data=merged).fit(cov_type='HC3') #regression(5)
drop_vars = [var for var in res_ols2.model.exog_names if var.startswith('state')]

def fixed_effects_indicator(model):
    if any(param.startswith('state') for param in model.params.index):
        return 'Yes'
    else:
        return 'No'
print(summary_col([res_ols1,res_ols2,res_ols3,res_ols4],
             model_names = ['(1)','(2)','(3)','(4)'],
             stars = True,regressor_order = ['shooting','fatality'],
             drop_omitted = drop_vars,
             info_dict={'Fixed Effects': fixed_effects_indicator,
                        '': lambda x: '',
                        'Observation': lambda x: str(int(x.nobs))}))
```

```
C:\Users\lenovo\AppData\Local\Temp\ipykernel_5520\3287299495.py:2: 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#re
turning-a-view-versus-a-copy
  MS['date'] = pd.to_datetime(MS['date']) # get the Mass Shooting date for each state
```

```
==================================================
                 (1)      (2)      (3)      (4)
--------------------------------------------------
shooting       0.5474*  0.5509*  0.8553*  0.8511*
               (0.3179) (0.3180) (0.4606) (0.4616)
fatality                         -0.0393  -0.0383
                                 (0.0284) (0.0289)
R-squared      0.0001   0.0003   0.0001   0.0003
R-squared Adj. 0.0000   -0.0009  0.0000   -0.0009
Fixed Effects  No       Yes      No       Yes

Observation    31738    31738    31738    31738
==================================================
Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01
```

From the regression results, we know that there is a positive relationship between mass shooting and CS popularity change. The coefficient is even larger when fatalities are included. The inclusion of state fixed effects in the regression models controls for state-level heterogeneity and provides more robust estimates of the relationship between mass shootings and CS popularity.

Interestingly, fatalities have a negative effect on CS popularity. One explanation is that high fatalities make some players feel sad about shooting so they will be less likely to play Counter Strike. This effect, however, is insignificant and small compared with the positive effect of Mass Shooting on CS popularity. Take the results from column(4) as an example, if there is a mass shooting with 10 fatalities, the effect on CS popularity will be $0.8511 - 0.0383 \times 10 = 0.4681$, which means the CS popularity will still increase by 0.4681 on average.

Overall, the regression results suggest that mass shootings have a positive impact on the popularity of CS.

3 Difference-in-differences (DID) analysis

In this step, we identify the causality of Mass Shooting on CS popularity change using DID strategy.

$$CS_{it} = \sum_{\tau=-4}^{5} \beta_\tau MS_i \times Date_t^\tau + \delta_i + \sigma_t + \epsilon_{it} \quad (7)$$

where:

- i denotes state, t denotes the month;
- δ_i denotes state fixed effect and σ_t denotes time effect;
- CS_{it} denotes the Counter Strike popularity for state i in month t;
- MS_i is a dummy variable, which equals 1 when there is at least 1 Mass Shooting events for state i (which means state i is in the treatment group) and equals 0 otherwise;

- $Date_t^\tau$ is a dummy variable that equals one for the τ months relative to the Mass Shooting month;
- ϵ is the error term.

We interact the treatment variable with each of the month fixed effects (relative to the treatment month), treating the states that never experience Mass Shootings as the reference group. The estimated vectors of β_τ reveal the differences between the treated and control counties during each month. If, for example, Mass Shootings increases CS popularity, then we would expect the estimated β_τ to be constant over time for years before a Mass Shooting happened because of the parallel trends assumption. We would also expect the coefficients to increase as a Mass Shooting happened.

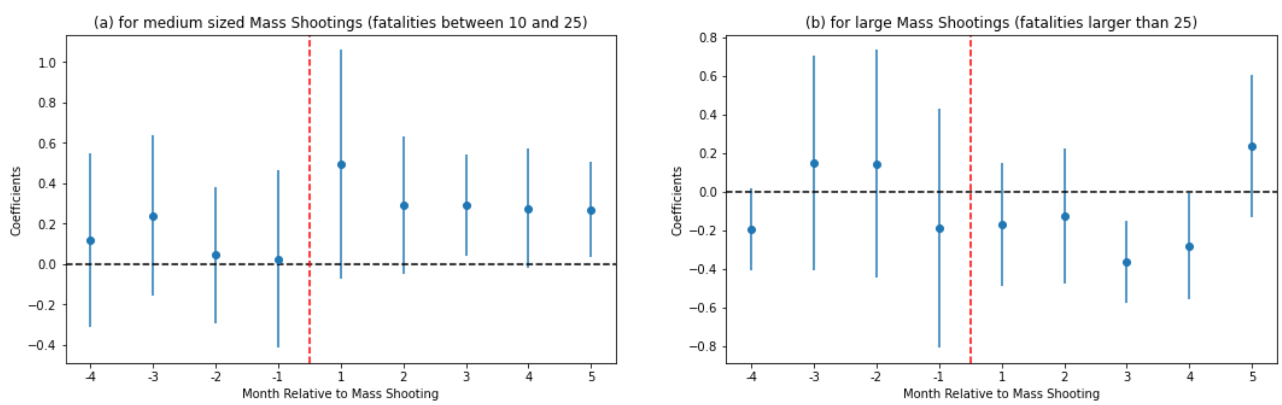
In [ ]:
```
def DID_regression(MS_data):
    merged_data = pd.merge(panel_data, MS_data, how='left', left_on=['state'],right_on=['Region'])
    data = merged_data.rename(columns={'CS popularity': 'CS_popularity'})
    data['time_diff'] = data['Month']-data['date']
    data1 = data[((data['time_diff'].dt.days >= -120) & (data['time_diff'].dt.days <= 180)) | (data['time_diff'
    data1['months_diff'] = np.floor_divide(data1['time_diff'].dt.days, 30) ## change it into months difference
    df_filtered = data1.loc[~data1['time_diff'].isna()]# extract rows where time_diff is not NaT
    data1 = data1[data1['Month'].isin(df_filtered['Month'].unique())]# extract all rows that contain Month valu
    dummies = pd.get_dummies(data1['months_diff'], prefix='p', prefix_sep='')# Create dummy variables for the '
    new_names = {old_name: f'p_{i+1}' for i, old_name in enumerate(dummies.columns)}# Rename the dummy variable
    dummies = dummies.rename(columns=new_names)
    data2 = pd.concat([data1, dummies], axis=1)
    formula = 'CS_popularity ~ Month + state + p_1 + p_2 + p_3 + p_4 + C(p_5, Treatment(1)) + p_6 + p_7 + p_8 +
    # Note that p_5 means the time of mass shooting.
    model = smf.ols(formula=formula, data=data2)
    result = model.fit(cov_type='HC3')
    params = result.params    # extract coefficients
    conf_int = result.conf_int() # extract confidential intervals
    return params,conf_int
```

Furthermore, we expect that different types of Mass Shootings may affect people differently. Section 2.2 shows, fatalities have a negative effect on CS popularity.Therefore, we define Mass Shootings with **fatalities between 10 and 25** as **medium** Mass Shootings and define those with **more than 25 fatalities** as **large** Mass Shootings. We use the two treatments respectively in regression(7) to investigate the effect of these two MS types on CS popularity.

In [ ]:
```
MS_medium=MS_events[(MS_events["fatalities"]>=10) & (MS_events["fatalities"]<=25)]
MS_large=MS_events[MS_events["fatalities"]>25]
params1,conf_int1=DID_regression(MS_medium)
params2,conf_int2=DID_regression(MS_large)

# draw parellel trends plot
fig, ax = plt.subplots(1,2,figsize=(18,5))
fig.suptitle('Figure 7. Parallel Trends Assumption Test',fontsize=18,y=1.03)
ax[0].errorbar(x=params1[-9:].index, y=params1[-9:].values,
               yerr=(params1[-9:].values - conf_int1[-9:].loc[:,0],
                     conf_int1[-9:].loc[:,1] -params1[-9:].values), fmt='o')
ax[0].axhline(y=0, linestyle='--', color='black')
ax[0].axvline(x=3.5, linestyle='--', color='red')
ax[0].set_xticks(np.arange(len(params1[-9:])))
ax[0].set_xticklabels(['-4','-3','-2','-1','1','2','3','4','5'])
ax[0].set_ylabel('Coefficients')
ax[0].set_xlabel('Month Relative to Mass Shooting')
ax[0].set_title('(a) for medium sized Mass Shootings (fatalities between 10 and 25)')
ax[1].errorbar(x=params2[-9:].index, y=params2[-9:].values,
               yerr=(params2[-9:].values - conf_int2[-9:].loc[:,0],
                     conf_int2[-9:].loc[:,1] -params2[-9:].values), fmt='o')
ax[1].axhline(y=0, linestyle='--', color='black')
ax[1].axvline(x=3.5, linestyle='--', color='red')
ax[1].set_xticks(np.arange(len(params2[-9:])))
ax[1].set_xticklabels(['-4','-3','-2','-1','1','2','3','4','5'])
ax[1].set_ylabel('Coefficients')
ax[1].set_xlabel('Month Relative to Mass Shooting')
ax[1].set_title('(b) for large Mass Shootings (fatalities larger than 25)')
plt.show()
```

```
C:\Users\lenovo\AppData\Local\Temp\ipykernel_5520\3029390220.py:6: 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#re
turning-a-view-versus-a-copy
  data1['months_diff'] = np.floor_divide(data1['time_diff'].dt.days, 30) ## change it into months difference
C:\Users\lenovo\AppData\Local\Temp\ipykernel_5520\3029390220.py:6: 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#re
turning-a-view-versus-a-copy
  data1['months_diff'] = np.floor_divide(data1['time_diff'].dt.days, 30) ## change it into months difference
```

Figure 7. Parallel Trends Assumption Test



From figure 7, we first notice that parallel trends assumptions are met since β_τ is insignificant for $\tau \in \{-4, -3, -2, -1\}$. Also, for Medium sized Mass Shootings, we notice that after the treatment, β_τ goes up and becomes significantly positive in month 3 and 5, which means that Medium sized Mass Shootings increase CS popularity.

Interestingly, for large Mass Shootings, we notice that after the treatment, β_τ goes down and becomes significantly negative in month 3, which means that large Mass Shootings decrease CS popularity.

This phenomenon can be explained by the intuition that Medium sized MS inspires players to play CS but large MS discourages them to do so out of their compassion for the victims. Another explanation could be that medium sized mass shootings are covered with less intensity on the news. As a result, the negative connotations of a mass shooting are not sufficiently received by people.

4. Conclusion

We start with observing the total number of Mass Shootings and Counter Strike popularity in **two maps** and a **scatter plot**, and find that states with high Mass Shootings number partly match the states with high high CS popularity. We then suppose that there is a causality between Mass Shootings and CS popularity.

We also do time series analysis through line graphs. Graphing mass shootings against CS popularity, states with mass shootings against states without, while also taking into account the dates of mass shootings events. After doing such analysis we find evidence of our hypothesis.

Then, we examine the correlation through some **preliminary linear regressions**. These regressions report that the coefficients we are interested in are significantly positive. Therefore, we find the correlation.For further study, we also analyze “similar” shooting activities,namely airsoft and laser tag, by running preliminary linear regressions. Through this we conclude there is no correlation, with mass shootings on laser tag or airsoft.

However, it is not enough to conclude that there exists causality. Thus we conduct **dynamic difference-in-differences**. We find the different effects of different types of Mass Shootings. Results show that medium sized Mass Shootings increase the CS popularity and large Mass Shootings decrease the CS popularity. One explanation is that people are inspired to play Counter Strike when there is a medium Mass Shooting in their state, but if a large Mass Shooting occurs, they feel sad for the victims and they are less likely to play Counter Strike.

In conclusion, medium sized mass shootings have a positive effect on Counter Strike popularity.

5. Future Study

Future work can explore more variables that could affect the popularity of Counter Strike, such as new game releases, changes in game features, and promotional events.

Additionally, the analysis can be extended to include other popular first-person shooter games to compare the trends in popularity over time. It may also be interesting to analyze the effects of online reviews and ratings on the popularity of the game.

Furthermore, the study can be replicated in different countries to determine if there are regional differences in the factors that influence the popularity of the game.

Moreover, this analysis only looked at short-term effects in the 5-6 months following a mass shooting. Future work could explore whether these effects persist over longer periods of time, and whether there are any longer-term consequences for CS popularity and the video game industry as a whole.

Lastly, given the limitations of the study, future work could consider alternative models or econometric techniques to address the potential issues of omitted variable bias and endogeneity.