**Title**

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**Introduction**

Automated speed control camera programs have been a staple of many European countries for many years and are being implemented into American communities by local governments. This research paper seeks to understand how these programs fair in the more car centric culture present in the United States. This was accomplished through the examination of the effects of the introduction of speed control cameras in the boroughs of New York on the number of traffic fatalities. Understanding the effects of these programs will help policymakers better understand how to keep the citizens the seek to benefit safer. Generally, the public does not advocate for policies that seek to restrict their freedoms in the name of safety. As such policy makers need to be confident that the actions they take and the resources they allocate will better protect the lives of the people in their communities.

The economic theory would predict that, theoretically, the implementation of these cameras should act as a deterrent for speeding, a leading cause of severe traffic accidents, thus lowering the number of people killed in car crashes. However, the deterrent effect, like all economic theory, expects that individuals behave rationally and speeding, with the potential for fines and increased danger to the driver and those around them, would not be considered rational behavior. This empirical study is based on the shift in behavior predicted by the deterrence effect, guiding the analysis of the effects of the introduction of speed cameras into New York Counties.

Understanding how transportation policy effects the behavior of drivers has been a continuous effort for many economists. *Speed cameras for the prevention of road traffic injuries and deaths*, Wilson et al (2010) was a large-scale meta-analysis of speeding camera programs from around the globe, which concluded that there was a reduction in the expected number of fatalities in markets where automated speed cameras were present. Due to the diversified nature of the locations studied, they did not estimate the magnitude of the reduction in deaths. A more focused paper, *Are multiple speed cameras more effective than a single one? causal analysis of the safety impacts of multiple speed cameras,* Li, Zhu, Graham, & Zhang (2020), examines the area a speed camera affected driver behavior within a network. They concluded that the presence of multiple cameras within a 200-meter radius decreased the amount of accidents that resulted in injury by over twenty percent.

**Methods and Data**

Using the historical records of fatal traffic accidents, grouped by county and year, provided by United States Department of Transportation, each reported accident was split into three categories: treated boroughs of New York, control counties, and a noncomparable group. Defining a control group was not straightforward, as New York City is unique in many ways. The one hundred counties with the largest populations were used to form the control group, because all the boroughs except Staten Island are within the largest hundred. The largest county, Los Angeles, was excluded from the analysis. It has the highest number of fatalities by a large margin, causing it to have an undesirably large effect on the trend of the control group. The speed camera policy went into effect at the beginning of 2014, the data spanned the timeframe of 2009 – 2019. Five years is an adequate amount of time to compare the pretreatment trends, in addition to the effects after the public had adjusted to the policy. Expanding the window of observation further would have resulted in data from the 2020 pandemic, which could have altered the analysis in many ways that would be difficult to understand. The comparison of the shift in trend of fatalities after the introduction of speed cameras into the New York boroughs provides an estimate of the effects of the policy implementation. The is analysis was conducted through the regression equation:

Fatalitiesit​ = β1 \* Treatedi​ ​+ ∑ βt \* Yeart + ∑ δn \* (Yeart​ \* Treatedi​) + County Fixed Effectsi­ +ϵit​

Where δn, the difference in the expected number of fatalities in yeart within the boroughs where speed cameras were introduced from the control group. One key assumption for δn to be interpreted as the causal effect of the introduction of speed camera is the trend of the number of fatalities before the program are the same, less random noise. This is examined in Figure 1, with a vertical bar to help illustrate when the program was implemented.

Figure 1

A graph with red and blue lines

Description automatically generated

The average number of fatalities per county does not show identical trends before treatment in 2014, within the control group there was a sharp decrease from 2009 to 2010, that was not present in the treatment counties. This was not considered significant enough to deter the use of the event study model because both groups had a slowly growing positive trend across the five-year period.

**Results**

Regression Results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| YEAR\_2009 | -3.559\* |  | treated × YEAR\_2009 | -1.241 |  | |  |
|  | (1.842) |  |  | (4.491) |  | |  |
| YEAR\_2010 | -7.527\*\*\* |  | treated × YEAR\_2010 | 2.327 |  | |  |
|  | (1.824) |  |  | (6.235) |  | |  |
| YEAR\_2011 | -6.796\*\*\* |  | treated × YEAR\_2011 | 1.996 |  | |  |
|  | (1.835) |  |  | (6.821) |  | |  |
| YEAR\_2012 | -1.871 |  | treated × YEAR\_2012 | -2.129 |  | |  |
|  | (1.427) |  |  | (4.011) |  | |  |
| YEAR\_2014 | -0.839 |  | treated × YEAR\_2014 | -8.161\*\*\* |  | |  |
|  | (1.518) |  |  | (2.847) |  | |  |
| YEAR\_2015 | 9.172\*\*\* |  | treated × YEAR\_2015 | -19.972\*\*\* |  | |  |
|  | (1.956) |  |  | (5.893) |  | |  |
| YEAR\_2016 | 17.925\*\*\* |  | treated × YEAR\_2016 | -30.925\*\*\* |  | |  |
|  | (2.159) |  |  | (8.905) |  | |  |
| YEAR\_2017 | 16.011\*\*\* |  | treated × YEAR\_2017 | -33.611\*\*\* |  | |  |
|  | (2.350) |  |  | (7.092) |  | |  |
| YEAR\_2018 | 15.505\*\*\* |  | treated × YEAR\_2018 | -35.105\*\*\* |  | |  |
|  | (2.246) |  |  | (4.698) |  | |  |
| YEAR\_2019 | 14.796\*\*\* |  | treated × YEAR\_2019 | -30.996\*\*\* |  | |  |
|  | (2.296) |  |  | (4.883) |  | |  |
|  |  |  | treated | -0.608 |  |
|  |  |  |  | (21.598) |  |