# COVID-19 Lockdown Measures' Effect On Traffic Accidents' Rate In the US

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Submitted to

Central European University

Department of Economics and Business



*In partial fulfillment of requirements for the degree of Master of Arts in Economics*

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Vienna, Austria

June 5, 2023

# ACKNOWLEDGMENTS

I would like to express my deepest gratitude to Professor Mats Köster for his invaluable guidance, expertise, and support throughout my academic journey. His insightful feedback and dedication have been instrumental in shaping my research.

I would also like to extend my appreciation to my colleagues, Daria Yermolova and Malaika Aggarwal, for their collaboration, encouragement, and the stimulating discussions we've had. Their input has been invaluable in expanding my understanding of the subject matter.

Lastly, I would like to thank my partner, Dennis Nebenmayer, for his unwavering support, patience, and understanding. His love and encouragement have been a constant source of motivation and inspiration.

I am sincerely grateful to all those who have contributed to my growth and success, and I am truly fortunate to have had such wonderful individuals by my side.

# ABSTRACT

This thesis investigates the impact of lockdown measures on road safety outcomes using a diff-in-diff framework. By analyzing accident rates within different time windows and controlling for state fixed effects and weekday variations, the study provides valuable insights into the effectiveness of lockdown measures in mitigating accidents. The results indicate heterogeneous effects depending on the time window examined. Within a $\pm$ 26-day window, accident rates increased significantly for the treated group, highlighting potential unintended consequences of the lockdown measures. However, within a $\pm$ 14-day window, accident rates decreased significantly, indicating the positive impact of reduced traffic volume and stricter safety regulations. The effects became statistically insignificant within a $\pm$ 7-day window, suggesting higher variability and the influence of other factors. These findings emphasize the importance of targeted road safety measures during periods of reduced mobility. Policymakers should prioritize traffic enforcement, public awareness campaigns, and infrastructure improvements to enhance road safety.

***Keywords***: COVID-19, lockdown measures, diff-in-diff, accident rates, traffic volume

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# Introduction

The COVID-19 pandemic and its associated policies, such as lockdowns and stay-at-home orders, have significantly impacted transportation and road safety. Traditional state-issued data on traffic accidents have limitations, including underreporting, incomplete records, and delays, which can introduce biases. However, a recent dataset utilizing navigation system APIs overcomes these limitations by providing real-time and comprehensive information on traffic patterns and incidents. This dataset offers broader coverage, captures minor accidents, and is less affected by reporting biases. It enables a more accurate analysis of the impact of COVID-19 policies on traffic accidents compared to state-issued data, which may not fully capture changes during the pandemic. The thesis aims to analyze the impact of COVID-19 stay-at-home order on traffic accident counts using a Poisson regression model and a difference-in-differences (DID) approach.

The thesis utilizes a Poisson regression model to analyze the daily accident count data. A difference-in-differences (DID) approach is employed to estimate the causal effect of COVID-19 policies on traffic accident counts by comparing changes between the pre-pandemic (2019) and pandemic (2020) periods. State fixed effects are included to control for state-specific characteristics, enabling a more precise estimation of the policy effect while accounting for state-level differences.

The results of the generalized linear model (GLM) regression show that all the estimated coefficients are statistically significant. The coefficients for the categorical variables representing different states indicate significant variations in the accident count across different states in the US. The range of state coefficients reflects the diverse effects of state-specific factors such as infrastructure, regulations, and other unique characteristics.

The coefficient of interest is the interaction term between the treatment variable and time dummies, which captures the average treatment effect on the treated states. In this study, the treated states are those with defined beginning and end dates of lockdown measures. The estimated coefficient for the interaction term is less than 10% in absolute terms, indicating that the average treatment effect on the treated states is limited.

This finding suggests that the implementation of lockdown measures during the COVID-19 pandemic had little impact on the traffic accident count in the treated states. It implies that other factors, such as reduced mobility or changes in driver behavior, may have played a more significant role in influencing the accident count during the lockdown period.

The study of the impact of COVID-19 lockdown policies on traffic accident counts is crucial in understanding the implications for public health and safety, economic costs, policy effectiveness, transportation planning, and individual behavior. This research contributes to understanding the economic implications of pandemic-related policies, informing public health and safety measures, policy effectiveness, transportation planning, and individual behavior during crisis situations.

In the following sections, I will present a comprehensive analysis of the topic at hand. The Literature Review will provide an overview of existing research, followed by the Dataset section where I will detail the data collection process. In the Empirical Strategy section, I will outline the methodology used, including the identification assumptions. The Results and Discussion sections will present and analyze the findings, leading to a conclusive summary in the Conclusion section.

## Literature Review

The National Safety Council, conducted a study in May 2020 to investigate the impact of reduced traffic and changes in driving behavior during the COVID-19 pandemic, (Council, 2020). Their estimates revealed concerning trends in the United States, shedding light on the paradoxical relationship between reduced traffic volume and increased fatality rates. Despite an 8% drop in the total number of roadway deaths compared to the previous year, fatality rates per miles driven increased by 14% in March, indicating that the emptier roads became more lethal. These findings highlight the need for further research to understand the underlying factors contributing to this phenomenon and to develop effective strategies for promoting road safety during times of crisis.

In this context, (Meyer, 2020) conducted a noteworthy investigation into the pattern of US traffic safety during the initial COVID-19 lockdown and explored the reasons behind the different trends compared to previous declines in traffic volume. Mayer's study revealed a surprising contrast to previous recessions where fatality rates declined alongside reduced traffic volume. Instead, during the lockdown, motor vehicle fatality rates, injury accidents, and speeding violations increased and remained elevated as traffic gradually returned to normal. Mayer proposed a theory that social distancing on highways may undermine compliance with social norms, leading to an increase in non-compliance and dangerous driving behaviors.

Mayer's research approach included analyzing national and local statistics on US traffic volume, traffic fatalities, injury accidents, speeding violations, and other indicators of vehicular driving behavior. He compared the data for the COVID-19 lockdown in parts of the USA in March 2020 with similar data from the 2008-2009 global economic crisis and other major reductions in traffic volume in the US. By conducting a comparative analysis, Mayer aimed to understand the similarities and differences in the impact of the COVID-19 lockdown on traffic safety.

The contradictory results observed in the literature regarding the relationship between reduced traffic volume and road safety during the COVID-19 pandemic make it an intriguing area of study. While (Lin et al., 2021) found shifts in accident proportions among specific demographic groups in Los Angeles and New York City, (Barnes et al., 2020) identified changes in accident composition in Louisiana. These variations emphasize the need for a nationwide analysis to comprehensively understand the overall impact of the pandemic on road safety.

Furthermore, the availability of API gathered data provides an opportunity to enhance the understanding of road safety during the pandemic. Such data includes records of even small accidents that may have gone unreported, enriching the dataset used for analysis. By conducting a nationwide analysis using comprehensive data, this study aims to contribute to the existing literature by investigating the impact of the COVID-19 pandemic on driving behavior, addressing the literature gap, and providing valuable insights for policymakers, law enforcement, and healthcare workers in promoting road safety during times of crisis.

Taking into account the findings of the NSC study and the theories proposed by Mayer, it becomes clear that the relationship between reduced traffic volume and road safety during the COVID-19 pandemic is complex and multifaceted. While a decrease in traffic volume might intuitively be expected to lead to fewer accidents, the observed increase in fatality rates suggests that other factors are at play. Mayer's theory of social distancing on highways undermining compliance with social norms offers a valuable framework for understanding this phenomenon. If his theory holds true, it would imply that the behavioral changes resulting from the pandemic, such as decreased social interactions and reduced law enforcement presence, may contribute to an increase in dangerous driving behaviors.

## Dataset

The paper describing the dataset creation process, "A countrywide traffic accident dataset" by (Moosavi et al., 2019), was published in 2019. However, it should be noted that the dataset was actively updated until May 2023, and the latest version available at the time of the dataset description process is the one from May 2023. The dataset used for the analysis in this thesis spans February 2016 and March 2023. The following paragraphs briefly describe the data collection process that was reported in the aforementioned publication.

The first step in creating the dataset was the collection of real-time traffic data. Two real-time data providers, "MapQuest Traffic" and "Microsoft Bing Map Traffic," were used. These providers offered APIs that broadcasted traffic events such as accidents and congestion. The data was captured by various entities, including the US and state departments of transportation, law enforcement agencies, traffic cameras, and traffic sensors within road networks. Data was collected every 90 seconds from 6 am to 11 pm, and every 150 seconds from 11 pm to 6 am. Over the course of the study at the publication date of the data collection method, which spanned from February 2016 to March 2019, a total of 2.27 million cases of traffic accidents were collected. MapQuest contributed 1.7 million cases, while Bing contributed 0.54 million cases. Currently, the count of records is much larger, with the same contribution shares of aforementioned navigation systems.

The next step involved integrating the collected data. Duplicate cases were identified and removed. Two events were considered duplicates if their Haversine distance (geographical distance) and recorded times of occurrence were both below specific threshold values. The distance threshold was set at 250 meters, while the time threshold was set at 10 minutes. These thresholds were chosen to ensure a very low possibility of duplicate records. Approximately 24,600 duplicated accident records, accounting for about 1% of the data, were identified and eliminated. After the removal of duplicates, the final dataset consisted of 2.25 million non-duplicated accidents.

Data augmentation techniques were employed to enrich the dataset with additional information. The first augmentation step involved reverse geocoding. Since the raw accident records only provided GPS coordinates, the Nominatim tool was used to translate the coordinates into addresses. The resulting addresses included detailed information such as street number, street name, relative side (left/right), city, county, state, country, and zip code.

Weather information was added to provide contextual data for the accidents. The Weather Underground API was used to obtain weather information for each accident. Raw weather data was collected from 1,977 weather stations located in US airports. Each weather observation record included attributes such as temperature, humidity, wind speed, pressure, precipitation (in millimeters), and condition. The closest weather station to each accident was identified, and the weather observation record with the closest reported time to the accident's start time was augmented with weather data.

Finally, the start time of each accident record was used to determine whether it occurred during the day or night. The "TimeAndDate" API was utilized, considering different daylight systems (Sunrise/Sunset, Civil Twilight, Nautical Twilight, and Astronomical Twilight) to assign the appropriate label.

## Empirical Strategy

In this thesis, I aim to analyze the impact of COVID-19 stay-at-home orders on traffic accident counts using a Poisson regression model and a difference-in-differences (DID) approach.

For sample selection, I focus on three time spans: 7, 14, and 26 days before and after the lockdown dates for both 2019 and 2020. However, a direct date-by-date comparison is not viable due to the mismatch in weekdays. To overcome this challenge, I address it by selecting accident counts for 2019 through a calendar date shift of 364 days from 2020. This adjustment accounts for the discrepancy in weekdays and is necessary due to the distinct patterns observed in accident counts based on whether the day is a weekday or a weekend.

To model daily accident counts, I choose a Poisson distribution as it aligns with the characteristics of the data. Accident counts represent whole number data, consisting of non-negative integers. Since regression techniques like Ordinary Least Squares Regression (OLS) are not suitable for such data, the Poisson regression model is appropriate. The data may exhibit a skewed distribution, with a large number of data points for only a few values. Additionally, accidents are relatively rare events, resulting in sparse data. This approach lies in lines with the recommendations in (Cameron & Trivedi, 2013). Considering these factors, the Poisson regression model allows me to estimate the rate of occurrence ($\lambda$) as a function of the explanatory variables and capture the relationship between these variables and the expected accident counts. Hence, the econometric model

I propose is as follows:

$$AccidentCount_{(state,year,day)} = Treated_{(state,year,day)} + PostTreatment_{(state,year,day)}$$
$$+Weekday + State + \lambda \times Treated \times PostTreatment$$

In the proposed econometric model:

1. $AccidentCount_{(state,year,day)}$: This is the dependent variable representing the daily traffic accident count in a specific state, year, and day. It is the outcome we are trying to explain and understand the impact of the variables in the model on.

2. $Treated_{(state,year,day)}$: This variable indicates whether a state, in a specific year and day, has implemented stay-at-home orders (the treatment). It takes a value of 1 if the state is treated and 0 otherwise.

3. $PostTreatment_{(state,year,day)}$: This variable captures the period after the implementation of stay-at-home orders in a specific state, year, and day. It takes a value of 1 for the post-treatment period and 0 otherwise.

4. $Weekday$: This variable accounts for any variation in traffic accident counts based on weather the day is a weekday or a weekend. This variable captures any systematic differences in traffic patterns and behaviors that may occur because of that. By incorporating it, we can control for these variations and isolate the effect of stay-at-home orders and the post-treatment period on accident counts more accurately.

5. $State$: This variable represents state-specific fixed effects. It captures any time-invariant characteristics of each state that may influence accident counts. By including state fixed effects, we control for unobserved heterogeneity across states

that could potentially confound the relationship between stay-at-home orders and accident counts.

6. $\lambda$: This term represents the rate of occurrence of accidents in a specific state, year, and day. It serves as the rate parameter in the Poisson regression model. The coefficients reported for $\lambda$ should be multiplied by 100 and interpreted as the percentage change in accident counts associated with a one-unit increase in the corresponding independent variable.

7. $Treated \times PostTreatment$: This interaction term captures the specific effect of the interaction between being treated (implementing stay-at-home orders) and the post-treatment period. It allows for an estimation of the differential impact of stay-at-home orders on accident counts during the post-treatment period compared to the pre-treatment period.

There are several reasons why the chosen specification of the econometric model is appropriate:

1. Identifying the treatment effect: By including the $Treated$ variable, we can isolate the impact of stay-at-home orders on accident counts. This helps address the key research question of assessing the causal effect of the policy intervention.

2. Accounting for temporal dynamics: The inclusion of the $PostTreatment$ variable enables us to examine the change in accident counts specifically during the post-treatment period. This accounts for the temporal dynamics and helps identify the short-term impact of stay-at-home orders on accident counts.

3. Controlling for state-specific heterogeneity: The inclusion of state fixed effects ($State$) accounts for unobserved time-invariant characteristics of each state that

may affect accident counts independently of stay-at-home orders. This helps control for potential confounding factors and improves the internal validity of the analysis.

## Identification assumptions

In the proposed econometric analysis, I assume that the necessary identification assumptions hold, despite recognizing that they might not be entirely true. These assumptions serve as a basis for establishing a causal relationship between stay-at-home orders and traffic accident counts. While there is a possibility of deviations from these assumptions, I proceed with the analysis under the assumption that they are reasonable approximations.

The key identification assumptions underlying the analysis are as follows:

1. Parallel Trends Assumption: I assume that, in the absence of stay-at-home orders, the accident counts in treated and control states would have followed similar trends over time. This assumption allows for a valid comparison between the treated and control groups. However, it is important to acknowledge that there may be factors influencing accident counts that are not accounted for, which could potentially violate this assumption.

2. Common Trends Assumption: I assume that the observed control variables capture any time-varying factors that influence both the treatment assignment and accident counts. While the inclusion of state fixed effects helps control for unobserved heterogeneity, it is important to recognize that there may be unobserved time-varying factors that are correlated with both the treatment variable and the outcome. Hence, there may be residual confounding that remains unaddressed.

3. Treatment Assignment: I assume that the assignment of stay-at-home orders is exogenous, determined solely by policy decisions. However, it is possible that endogeneity concerns exist, where states with higher infection rates or perceived risks were more likely to implement stay-at-home orders. While I acknowledge this po-

tential concern, I proceed with the assumption of exogeneity, recognizing that instrumental variable approaches or additional robustness checks could be employed to address endogeneity if necessary.

4. SUTVA Assumption: I assume that the treatment assigned to one state does not affect the potential outcomes or treatment effects of other states. However, there may be instances of policy spillovers or interdependencies that violate this assumption. The spatial correlation of accident counts and the potential for cross-state interactions should be considered, even though the assumption of no spillover effects is assumed to hold.

5. Non-Contamination Assumption: I assume that the implementation of stay-at-home orders in treated states does not influence accident counts in the control states. However, there is a possibility of information sharing or policy spillovers that could violate this assumption. Geographic proximity and communication channels between states should be considered, although the assumption of non-contamination is made for the analysis.

While these assumptions are made to facilitate the analysis, it is crucial to acknowledge their limitations. Empirical analysis always involves simplifications and assumptions that may not perfectly mirror the complex reality. Sensitivity analyses, robustness checks, and acknowledging potential violations of these assumptions would have provided a more comprehensive understanding of the results and their interpretability.

## Results

Taking into account the inclusion of state fixed effects and weekday indicators, we can observe additional insights regarding the changes in the coefficients for the interaction term (Treated:PostTreatment) when controlling for these factors. The results are as follows:

Within a ± 26-day window, after accounting for state fixed effects and weekday indicators, the coefficient for the interaction term remains positive and statistically significant at the 1% level. This suggests that the lockdown effect on the accident count rate is still positive and significant, indicating an increase in the accident count rate for the treated group compared to the control group during the post-treatment period. The magnitude of the effect, however, experiences a slight change in magnitude, with a coefficient of 0.073 instead of 0.094***. This indicates that after controlling for state and weekday effects, the lockdown effect remains statistically significant but slightly smaller in magnitude.

Similarly, within a ± 14-day window, the coefficient for the interaction term remains negative and statistically significant at the 1% level, indicating a significant decrease in the accident count rate for the treated group compared to the control group during the post-treatment period. However, when controlling for state fixed effects and weekday indicators, the magnitude of the effect changes to -0.028, which is slightly smaller compared to the unadjusted coefficient of -0.071**. This implies that even after accounting for state and weekday factors, the lockdown effect remains statistically significant but with an increased magnitude.

Lastly, within a ± 7-day window, the coefficient for the interaction term still becomes negative, but it loses statistical significance after controlling for state fixed effects and weekday indicators. This suggests that the lockdown effect on the accident count rate, within this narrower time frame, may not be statistically significant when considering these additional factors. The magnitude of the effect, after controlling for state and weekday effects, changes to -0.040**, indicating a potential decrease in the accident count rate for the treated group compared to the control group, although further analysis is needed to establish statistical significance.

In summary, the inclusion of state fixed effects and weekday indicators helps to account for variations across states and weekdays, providing a more comprehensive analysis of the lockdown effect on the accident count rate. Despite slight changes in the magnitudes of the coefficients, the overall findings remain consistent, indicating a positive and significant lockdown effect within a $\pm$ 26-day window and a negative and significant effect within $\pm$ 14-day window. However, the significance of the effect diminishes within the $\pm$ 7-day window when controlling for additional factors. These results emphasize the importance of considering contextual factors and controlling for confounding variables when interpreting the impact of the lockdown on accident rates.

## Discussion

Based on the observed results, we can see that there are varying effects on the accident count rate depending on the number of days before and after the lockdown. Specifically, a decrease of 4% and 6% in the accident count rate was observed at 7 and 14 days before and after the lockdown, respectively, while an increase of 8% in the accident count rate was found at 26 days before and after the lockdown.

These findings can be attributed to several potential factors. In the short term, the immediate implementation of the lockdown may have led to reduced traffic volume, decreased commuting, or changes in behavior that resulted in fewer accidents in the initial days following the lockdown. This could explain the observed decrease in the accident count rate at 7 and 14 days before and after the lockdown.

However, over time, individuals and society may have adapted to the lockdown measures. As people adjusted to the new circumstances, there could have been a relaxation of compliance with safety measures, increased movement, or changes in behavior that contributed to a rise in the accident count rate. This could explain the observed increase at 26 days before and after the lockdown.

It is important to consider other external factors that may influence the accident count rate, such as seasonal variations, changes in road conditions, or fluctuations in traffic patterns. These factors should be taken into account to accurately attribute the observed effects to the lockdown itself.

Additionally, it is essential to recognize that statistical variations and random fluctuations can also contribute to the observed differences in the accident count rate.

To gain a deeper understanding of these effects and provide a more conclusive explanation, further analysis should be conducted. This may involve considering additional variables and accounting for confounding factors that could potentially influence the accident count rate.

## Conclusion

This thesis has examined the impact of lockdown measures on accident rates within different time windows, employing a diff-in-diff framework and controlling for state fixed effects and weekday variations. The findings shed light on the complex relationship between the pandemic-induced lockdown measures and road safety outcomes.

The results indicate that the lockdown measures had heterogeneous effects on accident rates depending on the time window examined. Within a $\pm$ 26-day window, the analysis revealed a significant increase in accident rates for the treated group compared to the control group, suggesting that the lockdown measures may have inadvertently led to higher incidences of accidents. This emphasizes the need for comprehensive road safety strategies and increased traffic enforcement during periods of reduced mobility to mitigate potential adverse consequences.

Contrastingly, within a $\pm$ 14-day window, the lockdown measures demonstrated a statistically significant decrease in accident rates, suggesting their effectiveness in improving road safety during the pandemic. This finding highlights the potential benefits of reduced traffic volume, stricter safety regulations, and heightened public awareness of road safety.

However, within a $\pm$ 7-day window, the impact of the lockdown measures on accident rates became statistically insignificant at 5% level, while remaining statistically significant at 10% level. This suggests that the effects within this shorter time frame were subject to higher variability and influenced by other unaccounted factors. It underscores the importance of considering the broader context and understanding the limitations of the analysis.

The results emphasize the significance of incorporating state fixed effects and weekday variations to obtain a more nuanced understanding of the true effects of the lockdown measures. By controlling for state-specific factors and variations across weekdays, this thesis accounts for heterogeneity in accident rates and unveils important insights into the externalities of the lockdown measures.

In light of these findings, policymakers and relevant authorities should prioritize the development and implementation of targeted road safety measures during periods of reduced mobility. This includes maintaining traffic enforcement, promoting public awareness campaigns, and investing in infrastructure improvements to enhance road safety and minimize the unintended consequences of reduced traffic volume.

While this thesis provides valuable insights, it is important to acknowledge its limitations. The analysis is based on aggregate accident data, and the specific mechanisms driving the observed effects require further exploration. Future research could consider individual-level data and incorporate additional factors such as changes in driver behavior, road conditions, and traffic patterns to gain a more comprehensive understanding of the complex dynamics between lockdown measures and road safety outcomes.

In conclusion, this thesis contributes to the growing body of knowledge on the impact of lockdown measures on road safety. By employing a diff-in-diff framework and considering state fixed effects and weekday variations, the analysis offers valuable insights into the effects of the pandemic-induced lockdown measures on accident rates. The findings underscore the importance of comprehensive road safety strategies and highlight the need for continued research and evidence-based policymaking to ensure the well-being and safety of communities during unprecedented events.

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# Appendix

Table 1: Impact of Treatment on Accident Count within a ± 26-Day Window

| *Dependent variable: Daily Accident Count Rate* | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Intercept | 3.945*** | 3.793*** | 3.037*** | 2.791*** |
| | (0.005) | (0.015) | (0.009) | (0.016) |
| Treated | 0.014* | -0.014** | 0.012* | -0.019*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| PostTreatment | 0.065*** | 0.076*** | 0.058*** | 0.067*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Treated:PostTreatment | 0.094*** | 0.073*** | 0.097*** | 0.078*** |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Weekday | | | 1.106*** | 1.208*** |
| | | | (0.008) | (0.008) |
| State Fixed Effects | No | Yes | No | Yes |
| Observations | 3,154 | 3,154 | 3,154 | 3,154 |
| Pseudo-$R^2$ | 0.2287 | 1.000 | 0.9998 | 1.000 |
| Residual Std. Error | 1.000(df = 3150) | 1.000(df = 3117) | 1.000(df = 3149) | 1.000(df = 3116) |
| F Statistic | (df = 3; 3150) | (df = 36; 3117) | (df = 4; 3149) | (df = 37; 3116) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 2: Impact of Treatment on Accident Count within a ± 14-Day Window

| *Dependent variable: Daily Accident Count Rate* | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Intercept | 3.980*** | 3.761*** | 3.123*** | 2.848*** |
| | (0.007) | (0.021) | (0.011) | (0.023) |
| Treated | 0.069*** | 0.052*** | 0.070*** | 0.044*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| PostTreatment | 0.044*** | 0.065*** | 0.035*** | 0.056*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Treated:PostTreatment | -0.028** | -0.071*** | -0.028** | -0.062*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| Weekday | | | 1.041*** | 1.148*** |
| | | | (0.010) | (0.010) |
| State Fixed Effects | No | Yes | No | Yes |
| Observations | 1,730 | 1,730 | 1,730 | 1,730 |
| Pseudo-$R^2$ | 0.05487 | 1.000 | 0.9996 | 1.000 |
| Residual Std. Error | 1.000(df = 1726) | 1.000(df = 1693) | 1.000(df = 1725) | 1.000(df = 1692) |
| F Statistic | (df = 3; 1726) | (df = 36; 1693) | (df = 4; 1725) | (df = 37; 1692) |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 3: Impact of Treatment on Accident Count within a ± 7-Day Window

| *Dependent variable: Daily Accident Count Rate* | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Intercept | 4.008*** | 3.784*** | 3.163*** | 2.860*** |
| | (0.009) | (0.029) | (0.016) | (0.032) |
| Treated | 0.033** | -0.004 | 0.023* | -0.007 |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| PostTreatment | 0.019 | 0.042*** | -0.004 | 0.026** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| Treated:PostTreatment | -0.033* | -0.043** | -0.017 | -0.040** |
| | (0.018) | (0.018) | (0.018) | (0.018) |
| Weekday | | | 1.030*** | 1.175*** |
| | | | (0.015) | (0.015) |
| State Fixed Effects | No | Yes | No | Yes |
| Observations | 891 | 891 | 891 | 891 |
| Pseudo-$R^2$ | 0.0070 | 1.000 | 0.9993 | 1.000 |
| Residual Std. Error | 1.000(df = 887) | 1.000(df = 854) | 1.000(df = 886) | 1.000(df = 853) |
| F Statistic | (df = 3; 887) | (df = 36; 854) | (df = 4; 886) | (df = 37; 853) |

*Note:* *p<0.1; **p<0.05; ***p<0.01