NYC Congestion Pricing and Its Effects on Motor Vehicle Collisions
A Differences in Differences Analysis

Luke Catalano, Eleanor Stoever

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Abstract

This paper explores the effect of New York City's Lower Manhattan congestion pricing policy on traffic collisions in the district of Manhattan. Using data from the City of New York's Motor Vehicle Collisions-Crashes database, we will evaluate how the congestion pricing policy implemented on January 5th, 2025, has affected Lower Manhattan's total weekly collision count over the past 10 weeks. Employing a difference-in-differences approach comparing the congestion relief zone of Lower Manhattan to Upper Manhattan, we find a decrease of 20 total collisions where vehicle damage was greater than $1,000, or a person was injured, per week, representing a 16.66% reduction in the last 10 weeks from the average weekly collision count. This reveals the drastic effect of the congestion pricing policy on vehicle collisions and provides more evidence for the policy's existence.

I. Literature Review

This paper addresses the significance of congestion pricing in the Lower Manhattan area regarding motor vehicle collisions. Since this is a relatively new policy in the United States, there is not an extensive amount of research done on this topic. That being said, "The Short Run Effects Of Congestion Pricing In New York City" by Cook et. al., addresses a lot of the externalities associated with New York's congestion pricing policy. Using a Generalized Synthetic Controls model they found that the congestion pricing policy allowed for an increase in the average speed on both roads affected by the policy, and spillover effects onto reads that were not in the affected congestion pricing zone. Their findings suggest a decrease in CO_2 emission rates and delve into possible adverse effects of the congestion pricing policy on different marginalized groups in and around the affected area. They concluded that congestion pricing had a significant effect on all categories discussed above, with an emphasis on increased average speed. Although this research was intensive in the areas it observed, it failed to take into account the safety implications of congestion pricing regarding motor vehicle collisions and associated categories.

The paper "Congestion Pricing Policies and Safety Implications: a Scoping Review" written by Singichetti et. al., goes over a collection of congestion pricing policy implementations and proposed policies from around the world and their varied success. In collecting research to analyze, the authors found that there was a small amount of research on safety concerns related to congestion issues in large cities. Within this group of research concerned about public safety, they discovered that congestion pricing policies had similar effects on identical externalities, two of which were collision rates and pedestrian injuries/fatalities. The effects of congestion pricing policies on individuals' well-being differed depending on the relation of the individual to the congestion pricing policy zone. In focusing our analysis on collision rates specifically, instead of individual well-being, we can better understand the larger implications of the imposed congestion pricing policy in the Lower Manhattan area of New York City. Additionally, as our analysis is specific to New York, focusing on one key externality of the congestion pricing policy allows for a deeper dive into the specific effects of such policy.

II. Introduction

Traffic congestion in Manhattan, New York City, has been an issue for many years, lengthening the commutes of New Yorkers and increasing air pollution levels throughout the entire city (MTA, 2023). The NYC Congestion Pricing Policy seeks to limit congestion in the Lower Manhattan district below 60th Street by charging passenger vehicles up to $9.00 during peak toll hours. (Capparella, 2025) We identified that a decrease in vehicles may have additional unintended benefits to the community, such as fewer car accidents in the area leading to a decrease in vehicle-related injuries and possibly deaths in the area. This paper aims to understand how the congestion pricing policy that took effect below 60th Street in Manhattan on January 5th, 2025 affected the rate of motor vehicle collisions in the area. Understanding this effect will provide further evidence to other city and county governments on the effects of imposing congestion pricing on their city's most congested areas, a bold policy that has not been implemented in the United States prior.

The City of New York's Motor Vehicle Collisions-Crashes catalog data is used to employ a difference-in-differences regression analysis to estimate the effect of congestion pricing on weekly collision rates in Lower Manhattan. We will compare two very similar areas of Manhattan (Lower and Upper Manhattan) that would normally have parallel motor vehicle collision trends under the counterfactual that a congestion pricing policy was never implemented. For this analysis, Lower Manhattan below 60th Street is our treatment group, which has recently begun congestion pricing, and the remainder of Manhattan, referred to as Upper Manhattan, is our control group.

To provide a causal estimate with a difference-in-differences analysis between these two groups, the parallel assumptions trend must hold, where crash counts for both areas follow similar trends. To verify the parallel trends assumption, we plot the weekly crashes for both the treatment and control groups and can visually verify that Lower Manhattan and Upper Manhattan maintain relatively similar crash trends, with Lower Manhattan consistently having more accidents up until the policy initiation date of January 5th, 2025. We verify the balance between the treatment and control groups by establishing that the following pretreatment observable characteristics are near-identical. These characteristics are; average pedestrian injuries/deaths, average motorist injuries, and the average time of day an accident occurred. This balance supports the parallel trends assumption that the two groups were nearly identical prior to the treatment, and allows us to associate any significant difference in collision rates to the congestion policy implementation. We then ran a difference-in-differences regression, uncovering the estimated statistically significant decrease of 20 collisions where damage was greater than $1,000 or an individual was injured, per week in the treatment area of Lower Manhattan, attributed to the congestion pricing policy implementation.

III. Data

This study uses data from the City of New York's Motor Vehicle Collisions-Crashes catalog, maintained by the NYC police department. This data consists of motor vehicle collisions that resulted in the injury of an individual, or $1,000 worth of damage, making it well representative of the accidents that occur in NYC. It includes entries back to July 2012, but for this study, the months of January 2023 through March 2025 were utilized in the diff-in-diff assessment. We chose not to include 2020 through 2022 traffic collision data in the estimate due to a lack of congestion during the stay-at-home orders and the months following the COVID-19 pandemic, which is not representative of the current environment of NYC roadways. We chose to start with data from 2023 as the years closest to when the congestion pricing occurred would have been the most similar to those years, whereas years further away, i.e. 2012 or 2013, may have experienced different congestion trends. Data exists for accidents that occurred throughout all of New York City, however, we have created a subset of data containing only those that occurred in Manhattan using the borough variable, allowing us to easily split Manhattan into treatment and control areas for analysis.

The dataset includes information on the following; date of the crash, time of the crash, the borough and zip code in which the crash occurred, latitude, longitude, on-street name, off-street name, cross-street name, number of pedestrians injured, number of pedestrians killed, number of cyclists injured, number of cyclists killed, number of motorists injured, number of motorists killed, up to 5 different contributing vehicles, a collision ID, and the types of vehicles involved. We rely on numerous pre-treatment characteristic variables such as injuries, deaths, and time of day to validate treatment-control balance, and rely on individual row counts to establish weekly crash counts.

We are looking to identify a change in weekly accidents for the diff-and-diff assessment, so additional binning and data manipulation was needed to create the data frame for our final analysis. We choose to bin the data by weeks to properly quantify the difference for a meaningful time period, rather than the difference per day, which could be quite small. Our outcome of interest is crash count, representing the total number of crashes in a week. Our treatment group consists of crashes that happened in the congestion relief area of Lower Manhattan (below or at 40.7650° N), while the control group consists of those in Upper Manhattan (above 40.7650° N). The data included coordinate values for crashes, allowing us to match them to the treatment or control group. 40.7650° N is chosen as our threshold for the treatment and control groups, as the congestion pricing policy outlines 60th Street in Lower Manhattan as the cutoff for where tolls will begin to be charged. Figure 1 below shows the exact dimensions of both the treatment and control areas in NYC.

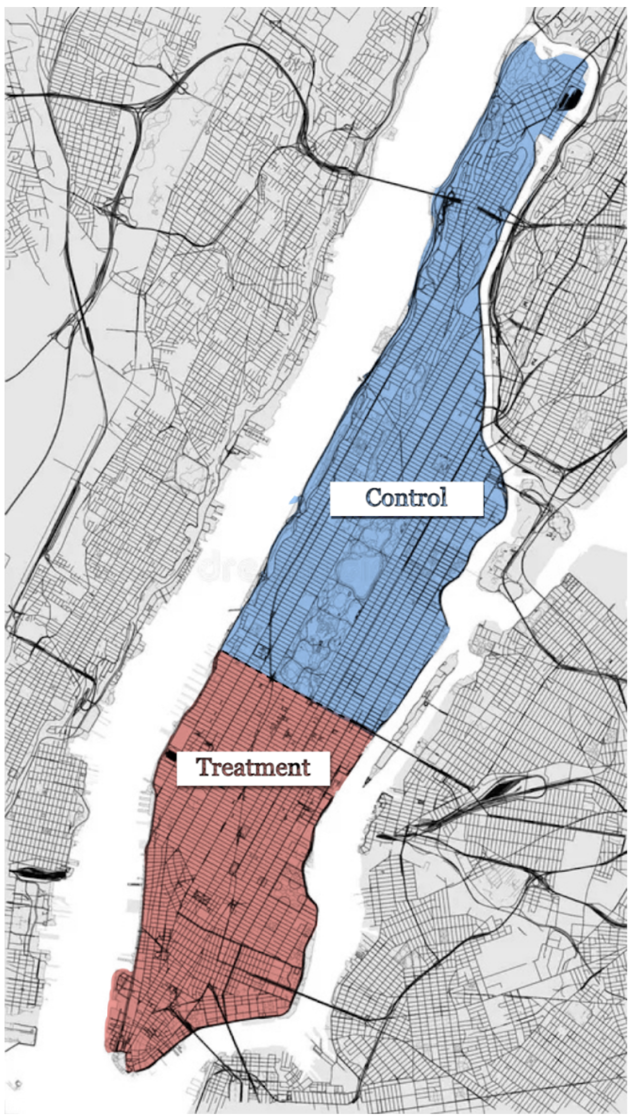

Figure 1: Enter Caption

Our final data consists of 115 weeks of collision data, 10 of which were after policy implementation. 2 rows represent each week; one row with the treatment group's total crash count, and a row with the control group's total crash count. The post variable was added to indicate whether a specific week was before (0) or after (1) the congestion pricing policy was implemented. Post_treat is an interaction term between the post and treatment variables, indicating whether or not an accident happened both in our treatment zone and during the congestion pricing period. This acts as our main difference-in-differences covariate in our regression model, and provides us with the effect of the policy on the treated area, after policy implementation.

IV. Empirical Methods

The primary empirical method for this analysis is a difference-in-differences regression approach, where we evaluate the differences in weekly crash counts between our treatment group of Lower Manhattan, below 60th Street, and our control group of Upper Manhattan before and after the implementation of New York City's congestion pricing policy. First, we evaluated the crash count trends for the treatment and control groups by plotting the weekly crash count for both groups from January 1st, 2023 to March 19th, 2025. Figure 2 shows that prior to the policy implementation on January 5th, 2025, our treatment and control groups experienced relatively parallel trends, with the occasional deviation from the trend seemingly due to random chance. We are confident that in the absence of a policy change, the trends would have remained similar enough to establish a causal estimate through a difference-in-differences approach.

We further verify the similarities between the treatment and control groups through a treatment-control balance table in Figure 3, comparing the averages of pre-treatment observable characteristics, such as the severity of injuries, who was injured, and the time of day between the control and treatment groups. Analyzing pre-treatment observable characteristics is important when conducting a difference-in-differences analysis, as one of the key assumptions of this method is that both the treatment and control group are nearly identical prior to the treatment occurring, or in this case, the congestion pricing being implemented. We find near-zero statistically insignificant differences at a 95% confidence level between the treatment and control groups and conclude that the two groups are essentially equal in terms in terms of available observational data, with the key difference between the groups being one having received the treatment of policy implementation and the other having not experienced a policy change.

With the parallel trends assumption met, and the similarities between pre-treatment observable characteristics verified through our treatment-control balance table, we can now use a difference-in-differences model to estimate a causal effect of the congestion pricing policy on weekly collision counts. For the difference-in-differences regression in this analysis, we will be estimating the robust heteroscedastic standard errors, as we know that the variance of the error term is not constant across time. This is usually the case with real-world data, as even miniature shocks to the crash count can alter the variance of the error term. This avoids any bias in statistical significance calculations that may stem from inaccurate standard error values, which is essential for providing a true causal estimate in this setting. Figure 4 is a regression table for the following difference-in-differences linear regression model:

$$crash\_count_i = 0 + \delta_0(post_i) + \beta_1(treat_i) + \delta_1(post_i * treat_i)$$

This model estimates the effect of the congestion pricing policy on weekly crash counts. The coefficient on the intercept is interpreted as a control group (Upper Manhattan) baseline weekly crash count before the policy change. The coefficient on the post covariate reflects the overall time effect, which is the difference in weekly crash counts in the control area after the policy change, and the coefficient on the treat covariate reflects the baseline difference in weekly crash counts before the policy change between the treatment area (Lower Manhattan) and the control area (Upper Manhattan). The coefficient on the interaction term between post and treat is our main difference-in-differences estimate, which represents the difference in weekly crash counts for the treatment area after the policy implementation date of January 5th, 2025. The difference-in-differences estimator in our regression is conceptually equivalent to the following:

$$\delta_1 = (\overline{Crash\_Count}_{post,t} + \overline{Crash\_Count}_{pre,t}) - (\overline{Crash\_Count}_{post,c} + \overline{Crash\_Count}_{pre,c})$$

In this equation, post indicates a value after the policy implementation, and pre indicates a value prior to the policy implementation. The variable t indicates the treatment group, and c indicates the control group. With the causality assumptions met, we can interpret the difference-in-differences coefficient on the interaction term as the causal difference in weekly crash counts after the policy was implemented, where we are taking the difference of the difference between Lower

Manhattan's post-treatment weekly crash counts & Lower Manhattan's pre-treatment weekly crash counts, and Upper Manhattan's post-treatment weekly crash counts & Upper Manhattan's pre-treatment weekly crash counts. The difference-in-differences linear regression model allows us to study the statistical significance of the diff-in-diff estimator when paired with the robust heteroskedastic standard errors, to ensure that the coefficient is statistically significant. Statistical significance in this case means our estimated difference is statistically different from zero, and the policy had a significant quantifiable impact on our treatment group. This is an important step of the empirical analysis processes, as a statistically insignificant difference-in-differences coefficient suggests that we cannot rule out the possibility that our treatment had a zero effect on our treatment group post-policy.

V. Results

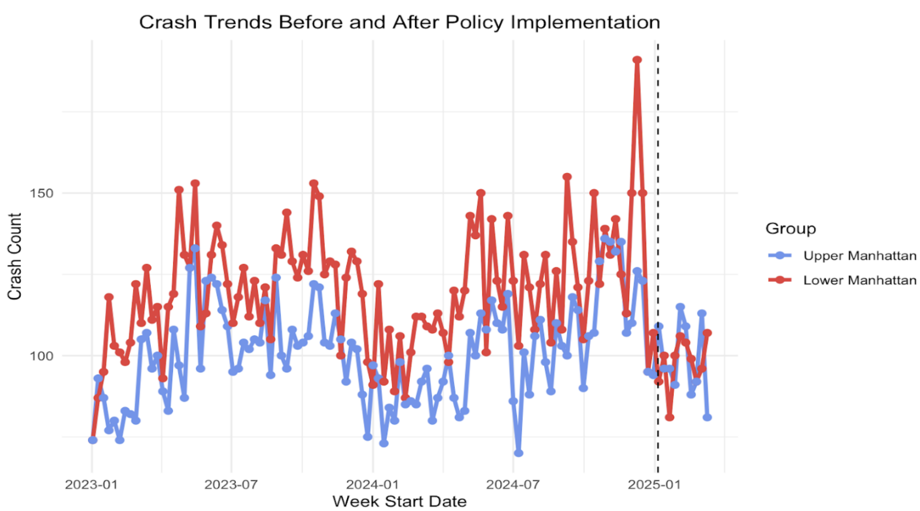

Figure 2: Treatment-Control Crash Trends

The parallel trends assumption is necessary to establish causal estimates through a difference-in-differences model and is met when our control and treatment groups follow similar trends prior to the treatment being applied to the treatment group. In this case, we are looking to verify that Lower Manhattan and Upper Manhattan have parallel weekly motor vehicle collision totals before the policy implementation on January 5th, 2025, throughout our desired time frame of January 1st, 2023 to January 4th, 2025. Before policy implementation, we can see that Lower Manhattan consistently had a higher frequency of crashes per week, but remained largely parallel to Upper Manhattan and that this trend is consistent from January 1st, 2023 to January 4th, 2025. After the policy implementation, it can be visually concluded that the trends of Lower Manhattan are no longer continuing with their original parallel trends with the Upper Manhattan area. We can see how Lower Manhattan's crash frequency is consistently in the range of Upper Manhattan post-policy, suggesting the two areas experience very similar vehicle collision rates after the congestion pricing policy implementation. While the treatment and control collision trends are not perfectly parallel, our date range is large enough for us to ignore minor inconsistencies, as there is likely to be a small number of outliers due to random chance. This visual verification led us to confirm the parallel trends assumption, a critical step in conducting our difference-in-differences analysis.

Treatment-Control Balance Table

	Control Mean	Treatment Mean	Treatment-Control Difference	
			Difference	*P-Value*
Hour of Day	12.92	12.94	-0.02	0.9926
Minute of Hour	25.59	25.77	-0.18	0.1931
Persons Killed	0.002217	0.0025	-0.000283	0.6535
Persons Injured	0.474	0.488	-0.014	0.1391
Motorist Injured	0.197	0.251	-0.054	0.6535

Figure 3: Treatment-Control Balance Table

Figure 3 shows that our pre-treatment observable characteristics of the treatment and control groups are nearly identical with statistically insignificant near-zero differences, essential to providing a good causal estimate. Had these differences been statistically significant

($p < 0.1$) we would be unable to claim that the control and treatment groups were near-identical in collision characteristics prior to the treatment, suggesting a difference in the types of collisions, and in turn, the frequency of collisions. The statistically insignificant near-zero differences suggest that any small variation between groups is most likely due to random variation. For this balance table, we chose to analyze the form of injuries that occurred as a result of an accident, including pedestrian deaths, pedestrian injuries, and motorist injuries. We see that Lower Manhattan and Upper Manhattan have near-zero, statistically insignificant differences of -0.000283 in average pedestrian deaths, -0.014 in average pedestrian injuries, and -0.054 in average motorist injuries throughout the pre-treatment period. Not only are these values statistically insignificant, but it is also not possible to have a non-whole number decrease in pedestrian/motorist injuries or in crashes as one can not have half of a crash or one-third of a person injured, so they should be effectively treated as zero. The treatment-control balance table also includes the average hour of day, and the average minute of the hour that accidents occurred for the treatment and control group, with statistically insignificant near-zero differences of -0.02 and -0.18, respectively. We gather from these results that the treatment and control groups have very similar motor vehicle crash injury results and occur on average at very similar times per day, allowing us to conclude that the main difference between our treatment and control groups of Lower and Upper Manhattan is that Lower Manhattan has experienced a policy change on January 5th, 2025.

Diff-In-Diff Regression for Weekly Crash Count

	(1)
Variables	**All Collisions**
Post	-2.114
	(3.8483)
Treatment	19.124***
	(2.3601)
Post*Treatment	-20.424***
	(4.8689)
Constant	101.114***
	(1.5206)
Observations	230

Robust Standard Errors in Parentheses

*** p <= 0.01

** p < 0.05

* p < 0.1

Figure 4: Diff-In-Diff Regression Table

Figure 4 is a regression table for our difference-in-differences linear regression model. Under the condition that the parallel assumptions trend is met, and our treatment-control groups are balanced to ensure they are nearly identical, this model provides us with a difference-in-differences causal estimate for the change in weekly crash counts for our treatment group of lower Manhattan after the policy is put into effect. This model is constructed on 230 data observations, 2 observations for each week; one for Lower Manhattan's weekly crash count, and one for Upper Manhattan's weekly crash count for 115 weeks total. The coefficient on the intercept acts as an estimated baseline measure for Upper Manhattan's weekly collision count at 101 crashes per week before the policy change. The coefficient on the post covariate is the overall time effect, or the difference in weekly crash counts in the control area after the policy change. This coefficient has a value of -2.114, suggesting a post-treatment decrease of 2.114 accidents per week for Upper Manhattan, but has a p-value greater than 0.1, suggesting that there is no statistically significant difference between crash counts in Upper Manhattan pre-policy implementation with 95% confidence. The coefficient on the treatment covariate reflects the difference in baseline weekly crash counts for Lower Manhattan before the policy change and Upper Manhattan before the policy change. This coefficient shows that on average, Lower Manhattan was experiencing around 19.124 more crashes per week than Upper Manhattan before the policy implementation. This coefficient has a p-value less than 0.01 and is considered statistically significant at a 95% confidence level. This is not a cause for concern for the validity of our parallel trends assumption, as we have established that Lower Manhattan consistently experienced higher weekly crashes, but did not deviate from its parallel path with Upper Manhattan. Our main difference-in-differences estimator is represented by the coefficient on the interaction between treatment and post, which is equivalent to taking the differences of the weekly crash count differences for the before and after-policy treatment and control location counts. The coefficient on our difference-in-differences estimator is -20.424, which is interpreted as a decrease of 20.424 motor vehicle collisions per week where vehicle damage was greater than $1,000 or a person was injured for the treatment area of Lower Manhattan, after the congestion pricing policy implementation. This coefficient is statistically significant at a 95% confidence level, with a $p < 0.01$, meaning we are 95% certain that there is a non-zero effect of the treatment on our treatment area of Lower Manhattan. We have a total of 20 observations after the policy implementation, or 10 weeks' worth of data, meaning that we could very likely see variation in this exact estimate. In the short run, it is shown that motor vehicle collisions have decreased in lower Manhattan due to the congestion pricing policy implementation.

VI. Conclusion

The city of New York has gone all in on relieving traffic congestion in Lower Manhattan through its congestion relief pricing program. These tolls, often reaching $9.00 per passenger vehicle during peak congestion hours, have led to a statistically significant decrease in overall collision count in Lower Manhattan at a 95% confidence level over the past 10 weeks. It has decreased the amount of traffic collisions by an estimated 20 collisions per week, a 16.66% decrease from the previous weekly average in this zone. While traffic collisions may have not been a target of the congestion relief pricing program, it is evident that congestion pricing has had a significant effect on the motor vehicle collision rates in this area, and thus the congestion pricing policy has had positive external effects in Manhattan. These results, paired with other benefits such as a reduction in vehicle emissions and an increase in revenue raised for the city of New York, make a compelling argument for the implementation of congestion pricing in other major cities.