Unintended Effects of Tax Hikes: from Ridership to Competition and Safety

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Abstract

This paper examines the effects of a 2019 congestion tax on rideshare usage in NYC. We use a difference-in-differences method to evaluate both the change in rides during this period and the coinciding decline in pick-ups. We find a significant decline in rides originating from the taxed area and a subsequent deadweight loss. We also measure a significant decline in collisions during this period and a reduction in injuries, suggesting that the policy has effects outside the rideshare market that partially counteract this deadweight loss. We also discover substitution between the competing services in the region.

1 Introduction

This paper examines a congestion tax implemented on taxis and rideshare programs in downtown Manhattan [26] designed to shift passengers into fewer vehicles and reduce overall traffic congestion. This tax is widely considered a "Phase One" of a larger tax designed to limit vehicles in the same area [22], and so offers critical insight into the consequences for NYC and the conjoined taxi and rideshare industry. We find strong evidence suggesting that the modest 2019 tax (ranging between \$2.75 and \$0.75 per passenger) does reduce pickups in the treated region, and further evidence that riders are more likely to pool rides after the tax. The overwhelming majority of this reduction in pickups is concentrated in yellow cabs. Rideshare programs have seen a much smaller reduction in rides in the treated area and may have even gained some of the pooled rides. Indeed, we find significant evidence that even green cabs appear to have filled in for this vacancy in (or at least very near) the treatment area, despite the fact that such operations are prohibited and heavily penalized by law. We attribute part of this substitution to the inflexibility of pricing schemes for yellow cabs - but we nevertheless see yellow cab fares decline by a significant amount, and yellow cabs appear to bear about 36% of the tax incidence.

Despite this inter-industry competition, regional safety appears to improve significantly within nearly every subset of collisions, fatalities, and injuries. We estimate that nearly 18 fatalities are prevented each year by this tax and about 518 injuries, spread across 1645 collisions. We do not find significant evidence of spillover collisions in border regions on the northern portion of Manhattan, suggesting that the future congestion tax may have minimal spillover impacts for congestion. However, the tax policy has a deadweight loss, an upper bound we estimate to be about \$250,000 per day on a tax revenue base of about \$1.16 million per day. This deadweight loss is partially diminished because many riders are substituting into pooled rideshare programs.

The reminder of this paper is organized as follows: in Sec. 2, we examine the relevant literature on congestion taxes and describe the background of the tax; in Sec. 3 we then examine the data available; in Sec. 4, we follow with a discussion of the methodology, a difference-in-differences approach; in Sec. 5 and Sec. 6, we examine the impact of the tax on rides and then secondary impacts on safety; in Sec. 7, then we use the results to derive an upper-bound estimate of the deadweight loss and total revenue, respectively; finally, in Sec. 8 we conclude with a summary of our results and direction for further research.

2 Background

2.1 Literature Review

Congestion taxes have long been considered an essential tool for controlling the externality of taxes. The earliest example of congestion tax proposals is [7] (found by [2]), a proposal in 1952 to price highway services "which will tend to eliminate the most obvious of the congestion evils in both the short and long run, namely, that of operating the road and street systems in a more efficient manner." Already, in [7] it seems Buchanan recognizes the possible benefit to urban areas, saying, "Our cities were simply not built to accommodate motor vehicle traffic of the magnitude now existing, and it is inconceivable to think of reconstructing them for this purpose." Fifty years later, these policies are being rapidly implemented in major urban areas and older cities [18], including New York City [6], Stockholm [11, 8], Sao Paolo [24], London [15], and Gothenberg [35]. Congestion taxes are widely considered the first-best or near-best solution at improving roadways' efficiency, e.g. [28].

More recent work has highlighted the association between ridesharing programs and congestion. In [3], authors find that the addition of ridesharing programs is associated with increased vehicle-miles traveled, excess gas mileage, and additional annual hours of delay in traffic. Critically, they find a 3% increase in fatalities and fatal accidents. A back-of-the-envelope estimation in terms of traffic fatalities founds a cost of these programs between $5-$13B.

Rideshare taxation specifically is a relatively new area of exploration. Lehe, et. al. [20] stands out as a case study for the Illinois state government. This paper summarizes the rideshare taxation policies of several major cities and states, as well as the revenues gained from several such policies. However, this report avoids examination of deadweight loss or any measure of these taxes' impact beyond revenue collection. In its first recommendation, this report urges the Illinois state government to pass legislation about ride-hailing taxes and impose a tax. State-level taxation is also the policy preferred by Uber - as stated in their 2019 lawsuit against the Village of Skokie, IL - citing patchwork local taxation. In [21], Lehe and Pandey highlight theoretical results that taxes or medallion costs may be required to obtain the socially optimum number of rides. The authors highlight that these taxes are so ubiquitous as to inspire an exercise in Milton Friedman's 1962 textbook. Liang, et. al. [23] have preliminary empirical results suggesting that rideshare taxation does indeed curtail rideshare demand by nearly 17 percent, but they only find a minimal impact on traffic congestion – a statistically insignificant increase in the downtown area. They do not explore the consequences for safety. Our study is one of the first available deep dives into the regional consequences of congestion taxes for the industry applied to relatively new urban ridesharing programs and serves as a "Phase 1" for the even larger congestion taxes planned for release within the same city.[13] We are the first to explore the inter-industry competitive effects of the tax and estimate the deadweight loss of the policy for the industry.

For several reasons, these anti-congestion policies are widely unpopular [12], at least upon announcement. First, they impose additional taxes. Evidence & theory, e.g. [19], both suggest that individuals will go through extreme efforts to avoid tolls even after their initial introduction – essentially, individuals are willing to pay to avoid costly tolls that were previously "free." Second, tolls raise concerns about equity and the potentially regressive nature of the tax.[30, 36, 17] In [31], authors highlights that there are diminishing returns to safety if one excessively reduces roadway traffic, which is also explored in [9] for NYC

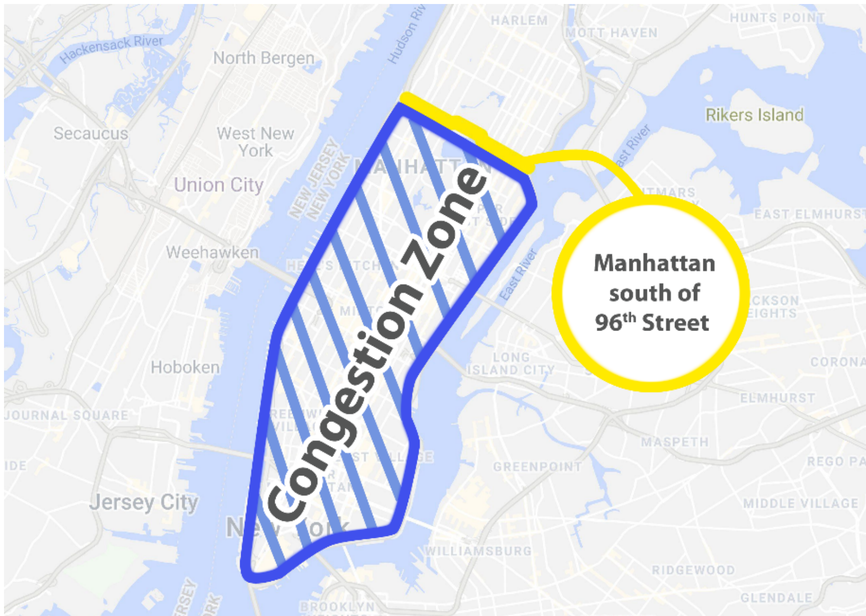

Figure 1: Area Targeted by the Tax, from NYC.gov

area. On the other hand, congestion taxes offer potential air quality [16] and safety improvements [32]. These policies also promise to direct resources towards underutilized public transportation, as highlighted in [22].

2.2 Implementation of the Tax

The NYC tax, implemented on January 1, 2019, targets rideshare vehicles and taxis with an eye towards reducing congestion in downtown Manhattan. The area of the tax is shown in Fig. 1, image courtesy of [26].

The fees are differential and designed to shift riders to share vehicles in so-called "pooled" trips. Curiously, it is not the realization of sharing a trip that designates a ride as pooled, but a rider willingness to share the trip. Therefore, a pooled ride may have only one passenger. This transition is encouraged by charging \$2.75 (the price of a subway fare) for rideshare trips in the region. If the individual chooses to take a taxi for the same trip, the fee is reduced to \$2.50. If there are multiple passengers, or the individual is willing to share the ride and indicates so, the ride is designated as pooled and the fee is reduced to 0.75 for each passenger.

Prior to our examination, we examine the data directly to confirm that there is a broad correlation between the region of most intense collision and the taxed areas. Fig. 2 confirms that the central mass of collisions is at the tip of the island of Manhattan, which is precisely where the tax is being applied. These taxed areas tend to be smaller in landmass and higher in population density.

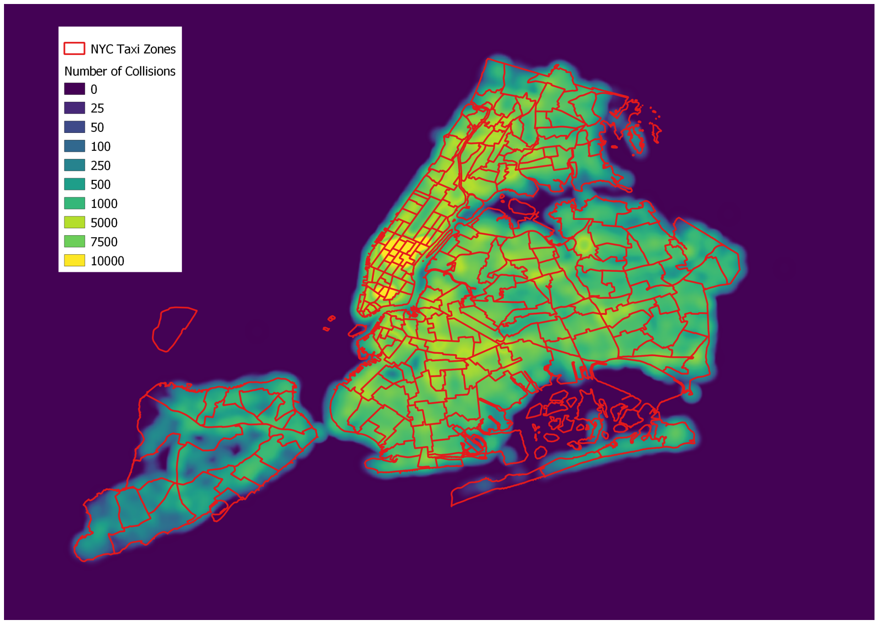

Figure 2: Hot Spots of Collisions and Taxi Regions

However, this merely confirms that collisions and the tax are occurring in the same zones, opening the possibility for an effective tax and effective reduction in collisions. It does not, by itself, demonstrate the tax will be effective or sufficient.

3 Data

In this section, we present the data sources used in this study. We considered two main data sets: rides and motor vehicle collisions. As we focus on analyzing the impact of the tax hike in NYC, we limit ourselves to rides data in the interval of time starting from January 2017 and extending to the end of December 2019, two years before and one year after the tax. In the remainder of this section, we briefly discuss each data set and its nature.

The first data set is the Motor Vehicle Collision data set [10], which contains the records of collisions occurring between vehicles within the city of New York. The data set is maintained and provided by New York Police Department under the NYC Open Data initiative, [27]. The NYC OpenData initiative is meant to provide free and transparent access to data from the city and the administration to residents and beyond. By New York City law, it is mandatory to report collisions where someone is injured, killed, or where there is at least $1000 worth of damage, which makes this data set a reasonably complete record of all collisions. Each record in the data set reports a single collision, specifically: the date and time of when it occurred; its location; the number of people injured or killed, broken down into motorists, cyclists, and pedestrians; the factors that contributed to the accident; and, the type of vehicles involved. Note that the data set does not include sensitive information that would allow one to trace back the people or cars involved in the collision or the report.

The second data set is what we refer to as the rides data set [33], which describes rides occurring in the City of New York performed via taxi and rideshare vehicles. As part of the open data initiative, the Taxi and Limousine Commission has been collecting and releasing data about rides in the city for many years. Such data spans from 2009 to the present day, and includes the yellow cabs, green cabs, Uber, and Lyft rides. The cab and rideshare data sets do not have the same structure; as a matter of fact, these are provided separately. The taxi data set is far richer than the rideshare vehicles, including data about fare breakdown, number of passengers, rate code, and more. The rideshare vehicles data set provides the pickup location, plus a flag denoting whether the trip was a pooled ride. In order to conduct our analysis, we created and unified and aggregated data set that focuses on the overlapping attributes between the two original data sets. We integrated all data in a single, de-normalized, data structure containing the fundamental attributes as well as additional summary data. Each record in our unified version is an aggregation describing the pickup information for each taxi zone each day. Specifically, the attributes composing each record are: the date and time of the trip start time, the rate code for the ride, the vehicle type (yellow cab, green cab, or for-hire-vehicle), the pickup location zone, and the number of pickups (for that day, hour, and zone). Note that location data from the original data sets are in part available as precise latitude and longitude, and in another part as a taxi zone in the city. This is due to a change in the policy for data collection following a public privacy concern around the possibility of identifying the habits of people.

Table 1 summarizes the general differences between taxed and untaxed regions. The taxed regions have high density, high traffic, and frequent transportation usage. Accordingly, the taxed regions represent a larger portion of rides (of all types) and revenues as measured by fares.

Although taxi rides in the untaxed zones tend to be less frequent, they tend to be much larger fares, typically having a similar number of passengers but going a longer distance. On the other hand, the total collisions (and other safety metrics) tend to be within ± 1 standard deviations between the two zones.

4 Methodology

The next several steps outline our approach to measure a plausibly causal connection between the tax and the subsequent decline in collisions.

First, we examine whether we have a suitable set of trends before and after the introduction of the tax. In Fig. 3, the aggregate trends in taxi pickups for both the taxed and untaxed areas appear to be consistent around the introduction of the tax. There is evidence of strong seasonality in taxi pickups,

Table 1: Summary of Ride Data

	Untaxed Zones		Taxed Zones		All Zones	
	Mean	SD	Mean	SD	Mean	SD
Trips, Single Cab	213	652	3466	2415	824	1747
Trips, Pooled Cab	63	247	1377	929	310	689
Trips, Single Rideshare	1365	2302	3826	2028	1827	2450
Trips, Pooled Ridehare	342	480	826	620	432	543
Passengers, Pooled Cab	201	778	4346	2943	980	2177
Passengers/Pooled Cab	3.18	0.79	3.15	0.10	3.17	0.70
Collisions	2.280	2.252	1.683	1.636	2.168	2.162
Cars in Collisions	4.407	4.433	3.222	3.190	4.185	4.252
Injuries	0.651	1.240	0.302	0.698	0.585	1.166
Deaths	0.003	0.052	0.002	0.052	0.002	0.052
Fare, Single Cab	$4,471.32	$21,433.02	$39,279.95	$28,267.80	$11,551.22	$26,921.76
Fare, Pooled Cab	$1,776.67	$10,018.94	$16,092.96	$11,979.67	$4,998.70	$12,076.11
Fare/Single Cab	$24.93	$47.31	$15.88	$8.93	$23.09	$42.57
Fare/Pooled Cab Passenger	$8.56	$8.02	$5.14	$1.18	$7.79	$7.22

N: 290,175; i = 265 (49 treated, 207 untreated); t = 1095.
Zones with no fares are omitted from fare estimation.

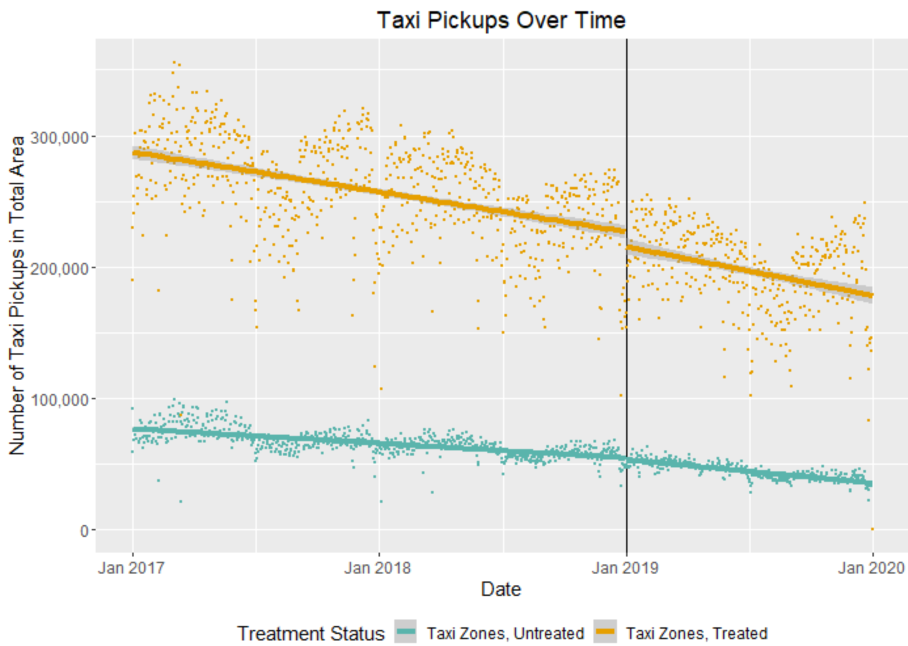

Figure 3: Parallel Trends for Taxi Industry

something we will account for with daily fixed effects across the 265 taxi zones. Our interest is in the modest decline in taxi pickups in the taxed areas relative to the (nearly nonexistent) shift in taxi pickups in the untreated areas. We examine several variations of this analysis, decomposing rides into both single and pooled rides, and then repeating it for rideshare programs.

We then explore if the congestion tax is associated with a meaningful change in the number of pickups in the treated region. Such pickup changes ought to occur prior to any anticipated change in collisions. We anticipate, as was the case in [34], demographic variables (which are typically measured annually or every census year) will only minimally change over the observation window. Therefore, for our examination, we will use a standard panel data difference-in-differences (DiD) examination.[1][1] This panel structure is intended to account for static differences in each of the taxi pickup districts or shifts over time.

The formula for this approach is as follows:

$$Rides_{it} = \alpha_i + \delta_t + \beta_1 taxApplies_{it} + \epsilon_{it} \tag{1}$$

In Equation 1, the fixed effects for taxi region i are α and the fixed effects for each time period t are δ. These fixed effects supersede the treatment group and treatment period interaction terms. We are interested in the coefficient β_1, attached to the variable $taxApplies_{it}$ that represents the relative change in rides

[1] Later, we will also consider a pooled analysis to examine the deadweight loss.

for the taxed group in the tax periods. Later, in Sec. 5.1, we further decompose this decline in rides by repeating this estimation on sub-samples restricted to each of the various competing types of services (yellow cab, green cab, and rideshare services), and competing types of rides (single and pooled rides). We find heterogeneous effects of the tax among the various programs. Explorations of the addition or removal of boundary regions in Table 7 that may experience spillover in rides show no meaningful changes.

After showing a significant decline in rides in the taxed area during the tax period, we next demonstrate that the region is reasonably safer after the tax. We do this by showing a decline in collisions under the same DiDstructure.

$$Collisions_{it} = \alpha'_i + \delta'_t + \beta'_1 taxApplies_{it} + \epsilon'_{it} \tag{2}$$

The results are shown below in Sec. 5, where the emphasis is on β'_1, the measured association between the tax and collisions. We supplement this evidence by further decomposing the collisions by all combinations of severity (fatality, injury), and participant type (pedestrian, cyclist, motorist). We show that all significant measures imply a safer area after the tax.

Finally, to estimate the deadweight loss, we pool the data together into two regions, treated and untreated. We also pool the data by month to reduce noise. With Equation 3, we perform a traditional pooled difference in differences estimation for each ride type:

$$\begin{aligned} Rides_{it} = \delta_0 + \delta_1 treatedRegion_i + \delta_2 treatedPeriod_t + \\ \delta_3 treatedRegion_{it} * treatedPeriod_{it} + e_{it} \end{aligned} \tag{3}$$

Our interest is δ_3, which estimates the change in the entire taxed taxi region at the time of treatment. Since we know the cost of the tax for each ride (\$2.50 for taxis and \$2.75 for rideshare services), we can directly estimate the triangular region of deadweight loss as $Tax * \delta_3/2$ under the assumption of static supply curves.

5 Results

5.1 Main Results

In Table 2, we explore the significance and impact of the introduction of the tax to lower Manhattan. Column 1 shows the relative decline in pickups in treated areas occurring at the introduction of the tax. We find approximately 1053 fewer pickups occur in each "taxi cab region." Specifically, Column 2 indicates a decline in the count of yellow cabs, representing the lion's share of the decline in pickups. Columns 3 and 4 represent a slight but significant uptick in pickups from the region's green and rideshare pickups. The increase is particularly curious in green cabs because it is forbidden by the green cab charter to pick up in this region, with a fine of \$500 and suspension for the first offense. On net, however, there is a total decline in pickups as shown in Table 2.

Table 2: Initial Changes in Pickups After Treatment In Treatment Period

	All Pickups	Yellow	Green	Rideshare
DiD	-1053.298***	-1137.013***	51.719***	31.995
	(-5.01)	(-11.69)	(5.66)	(0.15)
Const	3425.467***	1105.760***	88.402***	2231.305***
	(264.50)	(184.50)	(156.85)	(164.13)
R_a^2	0.866	0.945	0.860	0.694
N	290175	290175	290175	290175

Cluster-robust t-statistics shown in parentheses. ***:0.01,**:0.05,*:0.10

5.1.1 Inter-Service Competition

It appears that this policy has detrimentally affected pickups in general - but this decline is entirely shouldered by the yellow cabs - who have lost nearly 1200 pickups per month per zone in the treated area (nearly 56,000 yellow cab rides per month across the whole city). Indeed, Uber has made recent public statements [14] in cautious support of the congestion tax, something highly uncharacteristic for a private company taxed on its main source of revenue. Let us remind the reader that we only have pricing data for the cabs. It seems to be the case, at least anecdotally, that yellow cabs have a different price point than rideshare vehicles. The $0.25 cent difference between the single-ride fines might be insufficient to compensate for the greater pricing flexibility of the private rideshare vehicles. We note several news stories [4] indicating that Uber, a major rideshare company, is operating at a loss, which aligns with a narrative that Uber and other rideshares are quite elastic with regards to their pricing. We note there are numerous explanations outside of price that may have prevented the rideshare services from seeing the same declines. Some explanations amount to the yellow cab service having a different own-price elasticity. These explanations include but are not limited to ongoing marketing operations or public perception of service quality. We also note there could be simultaneous supply-side changes over this period, such as changes in the number of drivers per service, as drivers align themselves with whichever company provides the most regular work and highest compensation.

Regardless of the reason for the substitution between yellow cabs and rideshare programs, we still observe a modest but unexpected increase in the number of green cab pickups. Green cabs cannot street hail in this area; the areas green cabs can operate in are disjoint from the pickup area, see [25, 26]. Since pickups in this area appear to be prohibited by the charter of green cabs, one would expect no change. Yet, the exodus of the yellow cabs is followed by a modest but not insignificant number of green cabs operating outside of their chartered area, or at least operating close enough to the boundary that they are mismeasured as inside the region.

Table 3: Initial Changes in Pickups After Treatment In Treatment Period

	Single Rides		Pooled Rides	
	Cab	Rideshare	Cab	Rideshare
DiD	-807.609***	-192.673	-324.069***	68.280***
	(-11.02)	(-0.89)	(-11.26)	(3.67)
Const	860.617***	1894.722***	325.014***	504.666***
	(190.54)	(118.16)	(183.18)	(367.33)
R_a^2	0.937	0.646	0.945	0.855
N	290175	242210	290175	242210

Cluster-robust t-statistics shown in parentheses. ***:0.01,**:0.05,*:0.10
Pooled ride data is not available for rideshares prior to July 2017.

5.2 Transition to Pooled Rides

We note there are differential taxes on pooled and single rides. Both vehicle types have taxes such that single rides are generally discouraged, and pooled rides are cheaper (collectively and in total) than single rides. This appears to be by intention with a straightforward intuition: by motivating individuals to share rides, then less transportation will be needed, and congestion will be relieved. Using the same estimation procedure as the tables above, we then measure the transitions in ridership patterns for both cab and rideshare vehicles for variations occurring at the time of the tax. We note passenger data for rideshare vehicles is not available prior to July 1, 2022, so we omit these periods in this subset.

We find that there is a substantive and significant decline in single-rider cab trips in the treated area after the tax, with about 807 fewer single-rider cab trips per day per taxi region. There are also about 324 fewer pooled trips for cabs, suggesting a substitution away from the tax or a complementary resilience of pooled trips to the tax. On the other hand, the tax was larger for rideshare programs, so one might anticipate larger effects. In keeping with this intuition, we do find evidence of stronger substitution towards pooled rides in rideshare programs. For rideshare programs, there is only an insignificant decline in the number of single-rider trips of about 192 rides per region per day. However, there is a significant (but small) increase in pooled trips of about 68 rides per day per region. Combined, the columns in Table 3 highlight both the rapid substitution away from cabs after the tax and a clear substitution towards pooled rides from rideshare programs. The tax appears to have shifted the remaining passengers towards pooled rides, but primarily at the cost of the cab industry.

6 Congestion and Safety

After having established that pickups have declined in the treated area, we check to see if collisions have also declined. In Table 4, we show the results of that estimation, showing a decline in both transportation activity and collisions

Table 4: Simultaneous Reduction of Traffic and Collisions in Taxed Regions in Tax Periods

	All Pickups	Collisions	Cars In Collisions
DiD	-1053.298***	-0.092**	-0.169*
	(-5.01)	(-2.72)	(-2.56)
Const	3425.467***	2.139***	4.127***
	(264.50)	(1023.76)	(1013.38)
R_a^2	0.866	0.498	0.483
N	290175	290175	290175

Cluster-robust t-statistics shown in parentheses.
***:0.01,**:0.05,*:0.10

within the treated area. This suggests that the congestion tax is associated with improved safety in the region.

In the Table 4, column 1 shows that pickups decline significantly in the treatment region during the treatment period (by over 1053 pickups per treated region per day). Column 2 shows that simultaneously, in those same regions and time periods, the number of collisions declines by a significant 0.088 per zone per day, about 4.3 collisions per day across the entire city. Column 3 shows that the conjoined statistic of the number of cars involved in collisions also declines by a significant 0.165 per zone per day, so by all measures, we find a cohesive reduction in traffic and collisions, about 7.8 cars per day across the entire city. This comes to slightly less than 2 cars per collision.

In Table 5, we consider every type of casualty in the data set. First, we divide the casualties into injuries and fatalities, where we recognize injuries represent the vast majority of the casualties from collisions. We then again estimate the change in the treated area during the treated period, but this time targeting the changes in the various categories of injuries and fatalities.

We see in column 1 a significant decline in injuries of -0.021 per zone per day, and in Column 2, an insignificant decline in fatalities of 0.001 per zone per day. This comes to just over 518 injuries per year and 18 casualties over the same period. Then, we divide the casualties further into the type of vehicle being operated during the collision (if any). We find in columns 3 and 4 that the congestion law is associated with an insignificant decline in pedestrian injuries and fatalities. We also saw an insignificant decline in cyclist injuries (column 5), but the decline in cyclist fatalities was small and significant (column 6). Motorist injuries declined insignificantly (column 7), and we observed no decline in motorist fatalities (column 8). Overall, we find a cogent set of results: a significant decline in aggregate injuries, no significant increases in injuries or deaths in the treated region, and nearly all estimated coefficients were negative, except for one (Motorists Killed), which is essentially zero.

Table 5: Casualties by Type

	Injured	Killed	PedInjured	PedKilled	CycleInjured	CycleKilled	MotorInjured	MotorKilled
DiD	-0.021*	-0.001	-0.007	-0.000	-0.002	-0.000*	-0.012	0.000
	(-2.21)	(-1.10)	(-1.88)	(-0.36)	(-0.67)	(-2.31)	(-1.58)	(0.03)
Const	0.577***	0.002***	0.104***	0.001***	0.047***	0.000***	0.426***	0.001***
	(1004.73)	(82.33)	(429.37)	(51.91)	(321.46)	(24.34)	(940.73)	(67.89)
R_a^2	0.174	0.001	0.068	0.001	0.050	0.000	0.142	0.001
N	290175	290175	290175	290175	290175	290175	290175	290175

Cluster-robust t-statistics shown in parentheses. ***:0.01,**:0.05,*:0.10

6.1 Robustness Checks

In Table 6, we consider several explorations of our initial results. First, we consider that the tax has merely displaced traffic to the boundary of the taxed area. In problematic cases, this displacement might move the collisions rather than eliminate them. We note there are exceptionally few boundaries to consider since the treated area represents a literal island and it represents a significant effort to leave. At the same time, the new law treats only part of some regions (partially treated zones), and others just outside the treatment area (border zones), something that we explore here.

In column 1, we first check for any association between treatment and increased collisions in the border zones. We define a border zone as one adjacent to a treated taxi zone, but not itself treated. There are only two such zones, taxi zones 75 and 151, representing the northern component of Manhattan island. We check for this association by adding to Equation 2 a binary interaction of these border zones and the tax period, Border x TaxPeriod. This variable takes the value 1 in the border zones when the tax is active anywhere, and 0 otherwise. We estimate an insignificant increase in collisions along the border region, about 0.101 collisions per day per zone, about 1 collision every 5 days along the entirety of the city.

On the other hand, we observe a complementary insignificant decline in collisions in the zones that straddle the treatment boundary (indicated by the HalfTreated x TaxPeriod indicator). We interpret this as allowing for the possibility of modest collision spillover in the partially treated regions from the treated ones, i.e., that taxis and rideshare services prefer to pick up individuals who have stepped outside the boundary zone to avoid paying the tax.

Even after accounting for this, the measured in the treated zones remains significant and roughly the same magnitude (-0.085 collisions per zone per day). The remaining columns confirm this search by adjusting the treatment area by removing the various combinations of these boundary and half-treated zones. In column 2, we omit the half-treated region and find no meaningful change in the results. The primary treated region is still associated with significantly fewer 0.85 collisions per day per zone. Column 3 exhaustively drops all half-treated and border regions to avoid any potentially complicating factors from spillover. We find this has no meaningful impact on the coefficient of interest, which still suggests a significant decline in collisions of 0.85 per day per zone.

Last, in Table 7 we consider several different borough subsets to see if the subset choice has any effect on the number of collisions. Though the significance of the estimate varies, but the reduction falls within roughly the same range regardless of which boroughs are used as a subset.

In column 1, we include only Manhattan. The collisions have reduced by about 0.126 per day per zone, but the reduction is not significant. Including Brooklyn in column 2 shows a significant decline in collisions of about 0.108 collisions per zone per day. This point estimate changes very little in magnitude or significance in column 3 when we use the Bronx instead of Brooklyn. Using both Brooklyn and the Bronx in column 4 shows a negative and significant

Table 6: Robustness to Spillover and Ill-Defined Treatment Regions

	Including Border Interactions	Omitting Half-Treated	Omitting Both
Border X TaxPeriod	0.097	0.097	
	(1.24)	(1.24)	
HalfTreated x TaxPeriod	-0.107		
	(-1.26)		
DiD	-0.087*	-0.087*	-0.087*
	(-2.50)	(-2.50)	(-2.50)
Const	2.138***	2.143***	2.143***
	(1008.58)	(1020.16)	(1029.64)
r_a^2	0.498	0.499	0.499
N	290175.000	287985.000	285795.000

Cluster-robust t-statistics shown in parentheses. ***:0.01,**:0.05,*:0.10

Table 7: Collisions by Borough Subsets

Boroughs	Manhattan	Manhattan Brooklyn	Manhattan Bronx	Manhattan Brooklyn Bronx	Manhattan Brooklyn Bronx Queens
DiD	-0.126	-0.108**	-0.118**	-0.111**	-0.137***
	(-1.83)	(-2.83)	(-3.07)	(-3.24)	(-4.31)
Const	1.761***	2.242***	1.898***	2.210***	2.281***
	(103.30)	(456.32)	(327.46)	(672.91)	(1044.43)
r_a^2	0.401	0.503	0.401	0.480	0.485
N	72211	138945	118425	185159	259212

Cluster-robust t-statistics shown in parentheses. ***:0.01,**:0.05,*:0.10

decline of 0.111 collisions per day, an estimate that lies predictably between the inclusion of each zone separately. Finally, we exclude only Staten Island, a borough that is the furthest from Manhattan and has no direct automobile route or subway connection. After excluding this disjoint borough, we see a much larger decline in collisions of nearly 0.137 per zone per day. The exclusion of Staten Island (in particular) is meaningful since it does not have any automobile adjacency to the taxi zones. Under this lens, the decline in collisions is even larger than our primary measurements. In all subsets, the estimates show a decline in collisions within treated zones and the magnitude of this decline is consistently larger than our previously estimated decline of 0.85, suggesting we have selected a conservative comparison group.

7 Estimating Deadweight Loss of Policy

In this section, we abstract away from the nuances of within-industry competition and regional spillovers to estimate the aggregate deadweight loss of the congestion tax policy with respect to the destination-to-destination transit industry. We note that the intended consequences of the policy include more than just collecting tax revenue. In particular, we note that the improved traffic safety via reduced congestion serves to offset the public cost of the policy. We remind the reader that the estimated impact of the estimated 18 casualties and 518 injuries per year is nontrivial; simple estimates of the value of human life from [29] suggest this is over $57 million per year for the casualties alone.[2]

Aggregating the data by month in Table 8, we find a decline in cab rides within the treated area at the treated time of 38,945 rides per month (columns 1 and 2 combined). The decline in cab rides is composed of about 69% single cab rides (column 1) and 31% pooled rides (column 2). Including a simple time trend makes no substantive difference in this estimation.

The rideshare program also has lost 124,463 monthly rides on the net (columns 3 and 4 combined) but also observed a significant increase of 25,907 pooled rides per month during the period that has partially offset the substantive decline in single rides.

We have information on pricing for cabs but not private rideshare vehicles. Exploring the price information for cabs in column 5, we see fares decline (because rides are not perfectly inelastic) by about $0.90 per ride on average in the treated area for single-ride cabs (with no comparable FHV data available). Under the $2.50 surcharge, cabs pay 36% of the tax incidence, and the passengers pay the remainder (64%). There are few mechanisms for this price change except for shorter trips. Still, we suspect this is an overestimate of the amount paid by cabs because of the upcoming column 6. In column 6, we examine the change in the cost of pooled rides per passenger (assuming passengers split costs via cash or, with increasing frequency, electronic transfer). The tax is $0.75 per passenger, and we see an average of about 3.1 passengers per pooled trip for an average total tax of about $2.32 per pooled trip. However, pooled trip prices

[2] $3,186,408 * 18 for fatalities, noting they are not significant.

Table 8: Initial Changes in Pickups After Treatment In Treatment Period

	CabSingle	CabMulti	RideShareSingle	RideShareMulti	PSingle	PMulti
DiD	-26,701***	-12,244***	-150,343***	25,907***	-0.896***	-1.594***
	(-14.71)	(-19.39)	(-32.67)	(13.24)	(-5.10)	(-6.37)
Const	50,748***	14,980***	235,071***	98,279***	22.756***	24.086***
	(174.02)	(179.31)	(116.79)	(71.58)	(267.60)	(222.42)
R_a^2	0.903	0.931	0.784	0.499	0.866	0.877
N	2190	2190	1828	1828	2189	2188

Robust t-statistics shown in parentheses. ***:0.01,**:0.05,*:0.10

Table 9: Estimating Deadweight Loss

Category	Daily Estimated DWL	Ride Change	Tax Size
Cab Single	$33,376.25	-26,701***	$2.50/ride
Rideshare Single	$206,721.63	-150,343***	$2.75/ride
Cab Pooled	$14,224.26	-12,244***	0.75/Passenger
Rideshare Pooled	Undefined	25,907***	0.75/Passenger
Maximum DWL	$254,322.13		

***:0.01,**:0.05,*:0.10

have plummeted more than $1.50 per passenger - nearly double the tax itself. This overestimate suggests that the estimates of price decline in cabs might be capturing some other outside factor - such as a general struggle to convince passengers to take cabs relative to rideshare vehicles. We also note this is in line with earlier work [19] by Lehe and Devunuri, suggesting travelers are resistant to paying taxes on previously free activities - sometimes resulting in apparent overreactions to transit taxes.

The next step is to create a back-of-the-envelope estimate of the upper bound of the deadweight loss for these markets. By assuming linear supply and demand in the local area of the tax, we estimate the deadweight loss for all types of rides - except for pooled rideshare trips, which has increased ridership during this period. This inter-modal substitution diminishes or counteracts the deadweight loss; therefore, we call our estimate an upper bound. We expect that the price of rides is changing from the tax, even when hidden. Finally, we assume all other factors are held *ceterus paribus*.

As shown in Table 9, the upper bound of deadweight loss from this tax is about $254,322.13 per day, a sum partially offset by the privately held gains in value that have been recouped by the rideshare program's pooled rides. The constitution of this deadweight loss is found using the following following:

First, the vast majority of this deadweight loss (81%) comes from the decline in single passenger rideshare vehicles. As noted earlier, society will recoup some of this DWL by rideshares' nontrivial gain in pooled rides. The remaining deadweight loss centered within the cab market, divided so that the single-passenger cab market absorbs 70% and the pooled cab market absorbs the remaining 30%.

Finally, we then tally the total revenue from this tax. This is only an "estimate" to the extent that there may be disagreements between these statements and the financial statements of the city - we have all rides with no documented systemic exceptions. The total revenue is found by multiplying the value of the tax times the number of taxed rides. The annual revenue from this policy is about $425.7 million annually or $1.16 million per day. The composition of these funds is shown in Table 10.

This total of $425.7 million is 10% higher than the Metropolitan Transportation Authority's (MTA) forecast of $385 million annually [20, 5] (Metropolitan Transportation Authority 2018, II–37).

Table 10: Annual Revenue Breakdown By Source

Category	Revenue
Total Rideshare Single	\$210.4 million
Total Cab Single	\$128.5 million
Total Cab Pooled	\$47.3 million
Total Rideshare Pooled	\$39.5 million
Total Tax Revenue	\$425.7 million

8 Conclusion

In this article, we find several important effects of the congestion tax. First, it appears to work towards its intended effects, it is associated with a significant decline in pickups in the zone the tax is applied. This decline is roughly 52 thousand pickups per day, a decline centered primarily in single rides provided by yellow cabs.[3] Rideshare programs appear to be quite robust to this tax, and even appear to have significant gains in the number of pooled rides they deliver. We find evidence of the taxis having smaller fares after the tax is imposed - the decline in fare size is substantial and in the case of the single rides the incidence paid by cabs represents about 36% of the size of the tax. In the case of pooled rides, we see a supernormal decline in the price of fares which exceeds the per-individual tax which bears further investigation. Overall, we estimate an upper bound deadweight loss of nearly $250 thousand per day in the taxi zone. This deadweight loss is mitigated by substitution towards pooled rideshare programs, but more importantly is counterbalanced by the improvements in safety to the region. We find 18 fewer deaths per year in the taxed region and a significant 518 fewer collisions per year, a nontrivial benefit to the region. Finally, revenues from this tax are nontrivial, representing over $425 million to the city per year.

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