Taxation of Ride-Sharing Services in the Pandemic

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Abstract

Ride-sharing has disrupted the transportation market over the past decade. In this study, I examine Chicago's ride-sharing and taxi markets in two different contexts utilizing a regression discontinuity design. First, I quantify the effect of a new tiered congestion tax. The tax caused a 2-5 percent surge in the share of pooled rides, while congestion and taxi-riding behavior were unaffected. As a result, monthly tax revenue increased by at least $11 million. However, the effect was short-lived as the COVID-19 pandemic began just two months after the tax was implemented. Second, I examine the impact of the pandemic on ride-sharing and taxi markets. The pandemic caused a 5-9 percent drop in pooled rides, a 2-8 percent decrease in taxi cabs' share of the market, and a brief decrease in congestion. Further, the share of trips taken in downtown areas decreased by 4-20 percent, ride-sharing trips became shorter, and taxi tips fell by $0.45-0.97 per trip. The average monthly tax revenue for the city decreased by about 89 percent due to decreased utilization during the pandemic.

Keywords: Ride-sharing, pandemic, tax change, regression discontinuity
JEL: R40, H71, O33, L11

1 Introduction

E-commerce is no longer just a substitute for in-person retail nowadays. It has instead become a necessity, disrupting traditionally "offline" markets with a hybridization of brick-and-mortar establishments, which now operate in both online and offline channels. In transportation, for example, ride-sharing has become ubiquitous, easily surpassing the market share of traditional taxi cabs. Between 2014 and 2018, Uber and Lyft alone gained 72% of the private transportation market, while taxis and car rentals fell 36% each to 6% and 22% of the market, respectively (Richter 2018).

Although ride-sharing has consistently remained more popular than taxis in recent years, these applications have had their share of controversy. A number of disputes have developed, including contention over the characterization of drivers as employees or contractors (Sainato 2021), lawsuits over driver screening practices (Kelly 2016), allegations of price-fixing (CNBC Tech 2020), and issues with city traffic congestion. In fact, the City of Chicago recently implemented a tiered congestion tax on ride-sharing services in order to generate more revenue, improve public transit, and reduce traffic congestion (Henderson 2020). The new policy raises taxes on weekday rides in downtown areas during daylight hours.[2]

The tiered structure of the tax provides an opportunity to evaluate its effectiveness in revenue generation and congestion reduction by examining changes in consumers' riding habits. However, the tax is only observable for a few months before the beginning of the COVID-19 pandemic. The pandemic greatly affected ride-sharing firms and ride utilization.[3] In addition to examining short-term impact of the tax, I seek to quantify the effects of the pandemic on ride-sharing and taxi markets.

*Unless otherwise noted, figures and plots were produced by the author. All errors are my own.

[2]More details on the structure of the tax can be found on the City of Chicago's website here.

[3]In fact, Uber was forced to cut more than 3,000 jobs and consolidate many offices in order to survive (BBC News 2020).

The analysis relies on the universe of ride-sharing trips collected by the City of Chicago. Each individual observation is a trip with several useful variables recorded, including the cost (i.e. fare, tip, and additional charges), duration in seconds and miles, pick-up and drop-off location, and the number of other rides with which a trip was pooled. I augment the data with taxi utilization and pricing, traffic congestion metrics, and COVID-19 case reports.

The primary empirical specification is a regression discontinuity. I estimate both parametric and non-parametric designs in order to establish a causal link from the tax change. In the parametric design, I regress a number of response variables (e.g. share of pooled rides, share of taxi rides, congestion, etc.) on a treatment indicator for the congestion tax and several smoothing and control variables. In the non-parametric design, I use local linear regression and a numerically derived minimax estimator. The study of the pandemic includes similar parametric and non-parametric regression discontinuities with a univariate treatment indicator. The coefficient on the treatment indicator represents the average treatment effect. I explore heterogeneity in the treatment effects across several dimensions.

In the first section of the study, I find a 2-5 percent surge in the share of pooled rides. However, the tax did not significantly impact congestion or the share of taxi rides. The response to the tax was weaker in suburban and off-time (i.e. after 10:00pm and before 6:00am) rides with a 1 percent increase in the share of pooled rides in suburban areas. Subsequently, monthly tax revenue increased by at least $11 million. All results are robust to fixed effects, different kernels in non-parametric local regression, and various smoothing parameters in the minimax estimator.

In the next segment of the study, I discover a 5-8 percent drop in the share of pooled rides induced by the pandemic. Further, average speeds across the city increased by 0.4-1.3 miles per hour with decreased congestion levels. Finally, traditional taxi cabs' share of the market dropped by 2-8 percent as consumers preferred to use ride-sharing applications. Characteristics of ride-sharing and taxi trips also changed during the pandemic. The share of rides taken downtown decreased by 4-20 percent, average ride-sharing trip duration decreased by several minutes, and taxi tips decreased by almost $1.00 per trip. Average monthly tax revenue decreased by about 89 percent from post-tax change levels. The effects of the COVID-19 pandemic are most strongly felt in downtown areas of the city and during rush-hours. As above, all results are consistent in parametric and non-parametric robustness checks.

The remainder of the paper is organized as follows. Section 2 provides a background on ride-sharing services and the pandemic. Section 3 introduces the data and key variable construction along with some summary statistics. Section 4 and Section 5 describe the empirical specification and results, respectively. Section 6 briefly concludes.

2 Related Work

Recent studies have described a "retail apocalypse" in which brick-and-mortar stores without online sales channels have been forced out of the market (Hortaçsu and Syverson 2015). A similar trend is observable in other markets with the rise of the sharing economy. A vast literature examines the sharing economy—especially in transportation markets—and a rapidly expanding scholarship studies the effects of COVID-19. The two subjects pair naturally as the pandemic has forced consumers to convert to mostly online sales channels.

2.1 Ride-Sharing Markets

Many studies have examined ride-sharing markets in a variety of different contexts. Numerous articles have detailed the legal hurdles of integrating firms such as Uber and Lyft into existing transportation markets alongside taxis and other for-hire vehicles (Crespo 2016; Collier et al. 2018). Other papers have examined traffic congestion patterns resulting from the entry of ride-sharing firms (Li et al. 2017; Hall et al. 2018). Still other studies have evaluated the theory of competition behind ride-sharing markets and implications of flexible work (Nikzad 2019; Chen et al. 2019).

Perhaps the most influential papers have come directly from teams of economists at ride-sharing firms. A series of papers from Uber investigated the labor market for drivers, estimated consumer surplus generated from ride-sharing, and examined the gender earnings gap in ride-sharing drivers (Angrist et al. 2017; Cohen et al. 2016; Cook et al. 2018). Although these papers are statistically rigorous and rely on vast amounts of data, the implicit bias generated by using data from a single firm remains.

2.2 COVID-19 Pandemic

Unsurprisingly, the effects of the COVID-19 pandemic have been the subject of much recent research. In fact, the National Bureau of Economic Research (NBER) has collected more than four hundred working papers related to the pandemic. The body of work spans a wide range of topics, including asset markets, health, labor markets, and macroeconomic effects.[4] Researchers have found a decrease in center-city housing prices and rentals (Gupta et al. 2021), massive losses in brick-and-mortar retail sales and growth in online sales (Fairlie et al. 2021), and an increase in unemployment accompanied by a decrease in labor force participation (Cowan 2021). Another related paper found significant cannibalization of restaurant sales by online food delivery services (Collison 2020).

Several studies have examined the impact of the pandemic specifically on ride-sharing services. In a case study of Chicago, one paper found a significant reduction in ride-sharing utilization, which was larger than the overall reduction in traffic. Further, the authors find that single-rider trips were longer in terms of distance travelled (Du et al. 2020). However, this evidence was purely descriptive.

In this study, I make several contributions to the literature on ride-sharing services and the effects of the COVID-19 pandemic. Existing literature does not establish a causal link between the drop in ride-sharing utilization and the pandemic. Further, the recent implementation of the congestion tax in Chicago has not been studied and there is no in depth examination of its effects. I provide the first insights into the implications of the tax and the potential revenue lost due to the pandemic.

3 Data

3.1 Sources

The analysis leverages ride-level data covering the universe of ride-sharing trips in Chicago from 2018 to present. The data encapsulates approximately 200 million observations. A random sample of five percent (roughly 10 million rides) was used to ensure computational feasibility.

Each observation contains a number of useful variables related to costs, duration, and location of the trip. The fare, tip, and additional charges (including tax) are recorded, along with how many other trips with which the ride was pooled. It is important to note that the fare has been rounded to the nearest $2.50 and the tip has been rounded to the nearest $1.00. The time and mileage of the trip are also observable, along with the start time of the trip. The time is documented down to the second and the mileage is recorded to the nearest hundredth of a mile, while the start of the trip is registered to the nearest 15-minute interval of the hour. The data also includes the pick-up and drop-off community area of the ride. Each community area in Chicago is roughly a few square miles.

I supplement the data with several other sources. First, I use a five percent random sample (roughly 1.5 million rides) from a taxi trip dataset with the same variables and data constructs as above. Then, I use geographic data from Chicago to estimate latitude-longitude centroids of each community area. I use the centroids to construct a greater-circle distance from each pick-up or drop-off location to downtown Chicago. I further augment the analysis with traffic congestion estimates. The congestion data includes a timestamp, average speed, number of buses and cars, and location of the estimate. Finally, I utilize the Starschema database for daily COVID-19 case counts by location. Variables of interest include the date, county, positive cases, and deaths.

3.2 Variable Construction

The analysis relies on several important data constructs. In the data pre-processing steps, the time of the trip is split into the year, month, day, and hour, along with the day of the week and an indicator for whether the trip was taken on a weekend. The date is indexed over days by the set of positive non-zero integers with the first index being the first day of the sample. Community area latitude-longitude centroids were computed along with the greater-circle distance from the starting point and ending point to downtown Chicago.[5] Further, an indicator variable was added for whether the trip started or ended in a downtown community area. Finally, an indicator was added for trips that were affected by the new congestion tax imposed by the city on individual (i.e. not pooled) rides between 6:00am and 10:00pm on weekdays.

3.3 Descriptive Statistics

Prior to conducting any analysis, it is useful to consider some basic summary statistics of the sample. Table 1 reports descriptive statistics on the count, length, fare, and make-up of ride-sharing and taxi trips. The Appendix presents more granular summary statistics of different panels within the sample. Further, in order to have a valid study design, there must be an observable discontinuity in utilization after the onset of the pandemic and a discontinuity in the tax rate after the new congestion tax was implemented. Figure 1 confirms the presence of these two discontinuities.

[4]The NBER working paper collection can be found here.

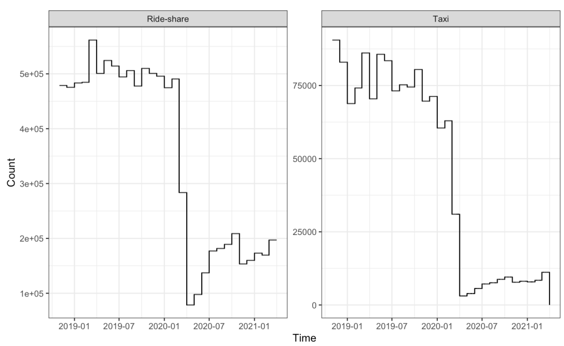
[5]This is done with the Haversine distance formula. More details can be found in the Appendix.

Table 1: Ride-Sharing and Taxi Descriptive Statistics

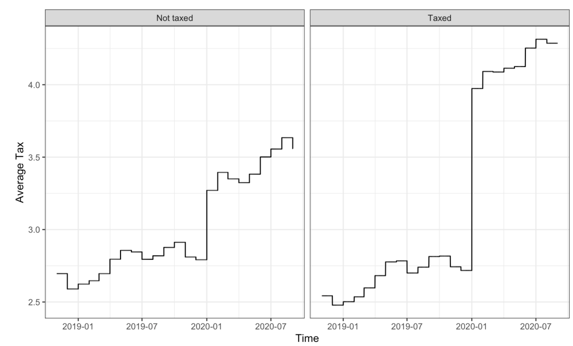
	N	Minutes	Miles	Fare	Tax	Weekend	Downtown	ΔN
Single Ride	9,044,738	15.04	4.70	\$10.62	\$3.13	32.53%	31.86%	- 146.89%
Shared Ride	1,134,867	22.00	6.48	\$8.05	\$1.62	28.68%	32.67%	*NA*
Taxi Ride	1,329,887	14.28	3.35	\$14.04	\$0.88	20.83%	56.00%	-905.93%

Notes: The table above summarizes ride-sharing and taxi activity in the analysis sample. ΔN represents the percent change in average monthly ride-sharing after the beginning of the pandemic. Notice that the *Shared Ride* entry is blank because shared rides were no longer permitted after March 17th, 2020.

Figure 1: Utilization and Tax Trends



(a) Utilization over Time



(b) Average Tax over Time

Notes: The two figures above were generated with a sample of ride-sharing and taxi trips in Chicago. The plot on the left shows ride-sharing and taxi utilization over time. The plot on the right shows the discontinuity in ride-sharing taxes after the implementation of a new congestion tax in Chicago.

4 Methods

I use a regression discontinuity design to estimate the causal effect of both the new tax on ride-sharing services and the pandemic. As a baseline model, I evaluate a typical parametric regression discontinuity:

$$\bar{y}_i = \alpha + \tau\delta_i + \sum_{k=1}^{3} \beta_k D_i^k [+\mathbf{X}_i] + \epsilon_i \tag{1}$$

where each variable is indexed by date i. The response variable $\bar{y}_i$ is one of the share of pooled rides, share of taxi rides, and measure of traffic congestion. D_i indexes the date. The δ_i term is defined as $\delta_i = \mathbf{1}[D_i > d]$ where d is the date index after which the treatment takes effect (i.e. the date after which the tax was implemented or the pandemic began). $\mathbf{X}_i$ is a vector of controlling variables and fixed effects.

In the tax analysis, the baseline regression is estimated only on pre-pandemic rides that start or end in downtown areas between 6:00am and 10:00pm because this is where the new tax was charged. In this specification, τ is the parameter of interest as it reflects the case when the treatment condition is met. Various robustness checks include different fixed effects, controlling variables, and filters on the data. These results can be found in the Appendix.

However, a parametric regression approach may have problems with bias and convergence. Thus, an alternative non-parametric approach is considered. I use two different non-parametric methods. The first is a typical local regression with a pre-specified kernel and bandwidth. The second is a numerically derived minimax linear estimator from Imbens and Wager (2019) which does not require a specific bandwidth or kernel. Bias-aware confidence intervals handle the issue of partial identification of the running variable (i.e. the index on which there is a cutoff value for treatment assignment). Robustness checks include testing different kernels, bandwidths, and bounds on smoothness. Details are included in the Appendix.

5 Results

5.1 Impact of the Congestion Tax

Overall, the implementation of the congestion tax resulted in a significant increase in pooled rides, but did not have much impact on congestion. There is mixed evidence on taxi rides. Table 2 presents the results of both parametric and non-parametric methods, including linear regression, local linear regression, and a numerically optimized minimax estimator. A battery of robustness checks can be found in the Appendix.

Table 2: Effects of Chicago's Congestion Tax

	Dependent Variable								
	Shared Ride			Congestion			Taxi Rides		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment Effect	0.021*	0.045†	0.043†	-0.163*	1.248	-0.444	0.019*	0.015	0.031
	(0.008)	(0.015)	(0.010)	(0.066)	(0.892)	(0.415)	(0.008)	(0.026)	(0.011)
Type	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*
Observations	28k	56	56	23k	45	45	23k	45	45
Day FE	Yes	No	No	Yes	No	No	Yes	No	No
Hour FE	Yes	No	No	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No	Yes	No	No

†p<0.01, *p<0.05

Notes: The results presented in this table show the effect of the congestion tax on shared rides, congestion, and taxi rides. Standard errors of OLS estimates are clustered at community areas as there is likely correlation of residuals.

The first three models in the table estimate the effect of the congestion tax on shared rides. The baseline linear regression in Column (1) shows that the share of pooled rides rose by 2.1 percent after the congestion tax was implemented. However, the parametric assumptions may lead to convergence or bias problems. Columns (2) and (3) do not rely on parametric assumptions. I find that the share of pooled rides rose by about 4 percent after the implementation of the congestion tax.

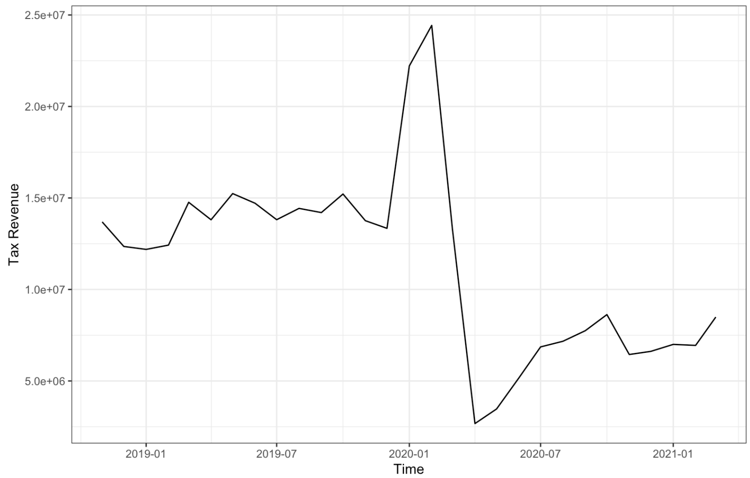
The next set of estimators evaluates the effect of the tax on congestion. The only statistically significant coefficient is found in the parametric model displayed in Column (4). However, the measure of the response variable is average miles per hour; 0.163 miles per hour, even if a non-zero estimate, is not a significant change in congestion patterns. The non-parametric models do not yield significant results, meaning there is likely no effect on congestion.

The final three models assess the impact of the tax on taxi rides. Column (7) reveals that the share of taxis rose by 1.9 percent after the tax. However, non-parametric methods reject this result. The local linear regression and minimax estimator in Columns (8) and (9) varied greatly depending on the choice of kernel, bandwidth, and smoothness, but were consistently insignificant. The significant coefficient on the ordinary least squares is likely an artifact of a heavy reliance on ride-sharing services around New Year's Eve. This suggests that there was was likely no significant effect on traditional taxi services.

The effects of the tax were felt heterogeneously across different types of riders. In particular, individuals in more suburban areas of the city only increased the share of pooled rides by about 1 percent compared to 2-4 percent. This is unsurprising given that there is an additional surcharge appended to the tax on downtown trips. Further, off-time rides (i.e. rides not during extended work hours) were not significantly impacted by the tax. Again, this is unsurprising given the structure of the tax.

After evaluating the tiered taxation scheme on the data sample, I find that tax revenue increased by at least $11 million. The increase is clearly displayed in Figure 2. Thus, the tax was effective in accomplishing one of its goals: to increase funding for public transportation. It was also able to increase the number of shared rides, yielding a positive environmental externality. However, these effects were very short-lived. The COVID-19 pandemic clearly disrupted ride-sharing utilization and the tax revenue generated. In the next section, I assess the impact of the pandemic on ride-sharing and taxi services.

Figure 2: Tax Revenue



Notes: Time-series of calculated tax revenue in data.

5.2 Impact of the Pandemic

The pandemic also resulted in significant changes in ride-sharing and taxi utilization. There was a massive decrease in the share of pooled and taxi rides coupled with a decrease in congestion. Table 3 displays the results of both parametric and non-parametric approaches, including linear regression, local linear regression, and a numerically optimized minimax estimator. A variety of robustness checks can be found in the Appendix.

Table 3: Effects of the Pandemic

	Dependent Variable								
	Shared Ride			Congestion			Taxi Rides		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment Effect	-0.085†	-0.056†	-0.067†	0.461†	0.513†	1.312†	-0.018†	-0.053†	-0.077†
	(0.005)	(0.013)	(0.010)	(0.071)	(0.117)	(0.108)	(0.005)	(0.008)	(0.006)
Type	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*
Observations	1.20M	883	882	849k	631	622	849k	631	631
Day FE	Yes	No	No	Yes	No	No	Yes	No	No
Hour FE	Yes	No	No	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No	Yes	No	No
Pandemic Control	Yes	No	No	Yes	No	No	Yes	No	No

†p<0.01, *p<0.05

Notes: The results presented in this table show the effect of the pandemic on shared rides, congestion, and taxi rides. Standard errors of OLS estimates are clustered at community areas as there is likely correlation of residuals.

As in the first set of results, the first three models of the table correspond to the share of pooled rides in Chicago. There was a significant decrease of 5-8 percent in the share of pooled rides after the pandemic began. In fact, ride-sharing applications briefly paused the "pooling" feature in March of 2020 due to the pandemic. The decrease in shared rides is robust to different methodology and controlling factors with the minimax estimator in Column (3) finding a 6.7 percent decrease in the share of pooled rides.

The next three columns present the effect of the pandemic on congestion in terms of average miles per hour in a given community area. The estimators consistently find an increase in average miles per hour on the road between 0.4-1.3 miles per hour. This is a more significant increase in speed than that of the taxation models, and there is no confounding by a major holiday event (such as New Year's Eve).

The final three models evaluate the impact of the pandemic on the share of taxis in the transportation market. The results consistently indicate a decrease of 1.8-7.7 percent of taxis' share of the market. This suggests that individuals preferred ride-sharing applications to traditional taxi cabs during the pandemic.

There is considerable heterogeneity in the effects of the pandemic. Most notably, shared rides, congestion, and taxi rides decrease the most in downtown areas of the city during rush-hours. Conversely, suburban areas and weekend rides were not affected as much. This reflects work-from-home policies: commuters were no longer required to travel to downtown areas—where a large portion of jobs are located—for work.

The characteristics of ride-sharing and taxi services were also affected by the COVID-19 pandemic. The share of downtown ride-sharing and taxi trips dropped significantly. Further, ride-sharing trips became shorter in terms of seconds, while taxi ride duration remained unaffected. Finally, tips to taxi drivers declined by nearly a full dollar per trip. Table 4 displays the results of both parametric and non-parametric approaches, including linear regression, local linear regression, and a numerically optimized minimax estimator. Robustness checks can be found in the Appendix.

Table 4: Effects of the Pandemic on Ride Characteristics

	Dependent Variable								
	Downtown Share			Duration			Tip		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ride-sharing Services									
Treatment Effect	-0.040†	-0.104†	-0.106†	-96.148†	-59.846†	-113.109†	-0.044†	-0.046†	-0.060†
	(0.003)	(0.020)	(0.020)	(7.165)	(21.853)	(10.051)	(0.011)	(0.013)	(0.013)
Taxi Services									
Treatment Effect	-0.051†	-0.200†	-0.222†	-11.750	58.147	-31.364	-0.434†	-0.516†	-0.974†
	(0.013)	(0.036)	(0.031)	(33.120)	(38.494)	(20.456)	(0.120)	(0.109)	(0.013)
Type	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*
Day FE	Yes	No	No	Yes	No	No	Yes	No	No
Hour FE	Yes	No	No	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No	Yes	No	No
Pandemic Control	Yes	No	No	Yes	No	No	Yes	No	No

†p<0.01, *p<0.05

Notes: The results presented in this table show the effect of the pandemic on downtown rides, duration, and tip. Standard errors of OLS estimates are clustered at community areas as there is likely correlation of residuals.

As above, the results are separated into sets of three models for each of the response variables. The first set of models shows the impact of the pandemic on the share of downtown rides for both taxis and ride-sharing services. In each mode of transportation, there is a significant decrease in the share of downtown rides. The share of downtown rides fell 4.0-10.6 percent for ride-sharing trips, whereas it fell 5.1-22.2 percent for taxis. Given that taxis are more prevalent in downtown areas, the result is unsurprising.

The next set of results displays the effect of the pandemic on trip duration in terms of seconds. There is a clear dip of 1-2 minutes in the duration of ride-sharing trips, but taxis are unaffected. There are several mechanisms that could be driving these different results. Taxis might be driving in areas where congestion was less affected, whereas ride-sharing services may direct drivers through less congested areas of the city. Alternatively, the client base of these two different modes of transportation may have shifted during the pandemic. The true explanation is not limited to these two options.

The final set of models reveals how the pandemic affected tips to drivers of both ride-sharing services and taxi cabs. The coefficient on ride-sharing tips, while significant, is only on the order of a few cents. On the other hand, the magnitude of the coefficient on taxi tips is 0.43-0.97, yielding a much more significant impact on drivers. Given that taxi drivers typically use driving as a primary source of income, the larger dip in tips is more consequential.

There is some heterogeneity in these results as well. The duration and share of downtown rides during rush-hours and weekdays were more significantly impacted than weekend and off-time rides. The heterogeneity is most visible in ride-sharing trips. This is likely due to the rise of work-at-home and lockdown policies that are affecting commuters.

The COVID-19 pandemic significantly affected the characteristics and make-up of ride-sharing and taxi services in numerous ways, including the share of taxi and downtown rides, congestion, and tips for taxi drivers. This is consequential not only for drivers' livelihoods, but also for the city in terms of tax revenue. The declining utilization and share of downtown rides means that even the new tiered congestion tax scheme could not recover all lost revenue. In fact, the average monthly tax revenue dropped by 89 percent due to the pandemic.

6 Conclusion

In this study, I analyzed ride-sharing and taxi services in two different contexts. First, I examined a new tiered congestion tax on ride-sharing services in Chicago. The tax successfully influenced riders to pool trips more often, but did not significantly impact congestion or push riders to use traditional taxi cab services. The effect on pooled rides was most clearly seen in downtown areas of the city and during work hours. Since the tax is structured to put the burden on these types riders, the result is unsurprising. The tax not only has positive environmental externalities, but it also helped the city generate millions more in tax revenue to improve public transportation. In the coming years, improved public transit should further influence riders to substitute busses and trains for individual ride-sharing or taxi trips.

Although the tax significantly improved revenue and generated positive externalities through increased pooled rides, the effects were short-lived. The COVID-19 pandemic nearly shut down ride-sharing and taxi services as economies began lockdowns and the death toll rose. The second portion of the study quantified the impact of the pandemic on ride-sharing and taxi services. There was a massive drop in the share of pooled and downtown rides and taxi cabs' share of the market. Further, the duration of ride-sharing trips and taxi cab tips decreased significantly. The effects were most clearly visible during rush-hours and the work week. The increasing numbers of individuals working from home were likely influential in the differential effects. The COVID-19 pandemic has also negatively impacted the city. The tax revenue generated from ride-sharing services was nearly cut in half during the pandemic.

These findings, while limited to just one city, show the short-term effects of tiered taxes on ride-sharing services and the devastating economic effects of the pandemic on drivers and cities.

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A Appendix A

Data and Methodology

A.1 Tiered Congestion Tax

There is a hierarchical structure to Chicago's new congestion tax on ride-sharing services. It relies on several ride characteristics including if the ride is pooled, goes downtown, ends in a special zone, or is in a wheelchair accessible vehicle (WAV).

Table A.1: Tiered Tax Scheme

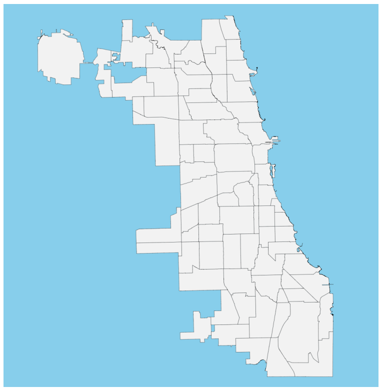
Single Ride			
	Previous Tax	*New Tax (No Downtown)*	*New Tax (Downtown)*
Standard	$0.72	$1.25	$3.00
Special Zone	$5.72	$6.25	$8.00
WAV	$0.62	$0.55	$0.55
Pooled Ride			
	Previous Tax	*New Tax (No Downtown)*	*New Tax (Downtown)*
Standard	$0.72	$0.65	$1.25
Special Zone	$5.72	$5.65	$6.25
WAV	$0.62	$0.55	$0.55

Notes: The table above summarizes the new congestion tax schema in Chicago. Standard rides are rides that do not start in special zones (e.g. downtown or airports) and WAV are wheelchair accessible vehicles. The downtown surcharge takes effect between 6:00am and 10:00pm.

A.2 Variable Construction

The analysis relies on several important data constructs outside of the key variables that are already included. First, I extract the day of the week from the date and create an indicator for whether it is a weekday or weekend. Next, I add an indicator for whether the ride took place in a downtown community area (community areas 08, 28, and 32), and an indicator for whether the ride was taken during daylight hours (6:00am to 10:00pm). I construct an indicator for whether the ride was subject to the new congestion tax: if the ride was taken during daylight hours during a weekday and started or ended in a downtown community area, then it had an additional tax.

Figure A.1: Chicago Community Areas



Notes: The figure above was produced with a shape file and depicts the community areas in Chicago.

The community areas are discrete measure (e.g. 08, 28, and 32 are all very close to one another in downtown Chicago). I calculate the distance from each community area to the center of downtown Chicago. The distance is calculated as the greater-circle distance from the latitude-longitude centroid of the community area of interest to a preset latitude-longitude pair for the center of downtown Chicago. The community area centroids are extracted from a labeled GIS database and the center of downtown Chicago is found as the latitude-longitude pair $(41.8781, -87.6298)$. The distance between the centroids and the center of downtown Chicago is found using the Haversine distance formula, which calculates the greater-circle distance between two latitude-longitude pairs in kilometers. The formula is given by

$$d = 2r\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}$$

where (φ_1, λ_1) and (φ_2, λ_2) are the latitude-longitude pairs of the two points of interest. The continuous measure d allows an index over which to run a regression discontinuity. The community zones for downtown Chicago all fall within 2.4 kilometers of the center of downtown Chicago so a cutoff value of $c = 2.4$ is used for this purpose.

The collected congestion data is sparse and required imputation of traffic speeds. In order to do this, I find the geographically closest community area with a traffic speed measurement and use this value. The Haversine distance formula is used to find the closest community area.

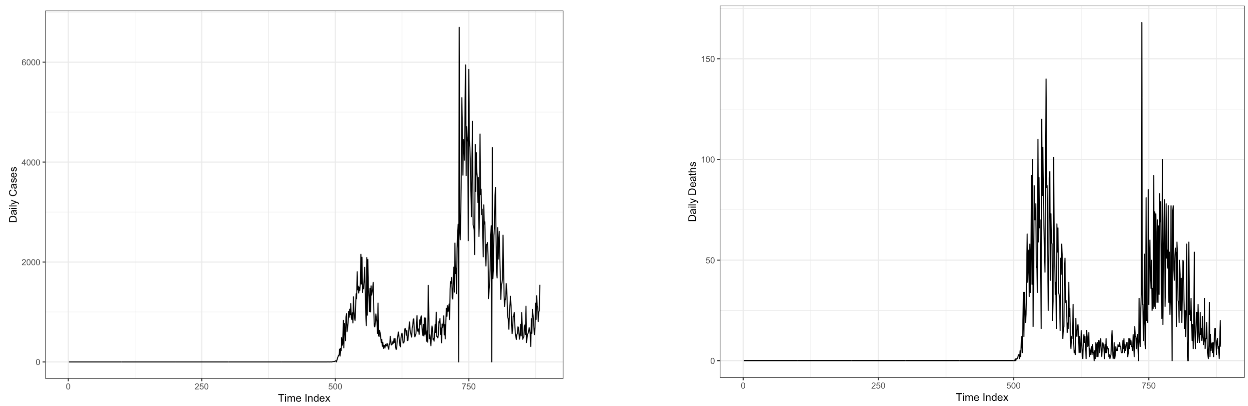
A.3 Descriptive Statistics

Table A.2: Paneled Ride-Sharing and Taxi Descriptive Statistics

		N	Minutes	Miles	Fare	Tax	ΔN
All	Single Ride	9,044,738	15.04	4.70	\$10.62	\$3.13	-146.89%
	Shared Ride	1,134,867	22.00	6.48	\$8.05	\$1.62	*NA*
	Taxi Ride	1,329,887	14.28	3.35	\$14.04	\$0.88	-905.93%
Weekend	Single Ride	2,942,155	13.95	4.49	\$10.34	\$2.94	-169.28%
	Shared Ride	325,503	20.84	6.69	\$8.34	\$1.61	*NA*
	Taxi Ride	276,988	13.82	3.53	\$14.60	\$1.17	-883.26%
Weekday	Single Ride	6,102,583	15.57	4.80	\$10.75	\$3.23	-143.42%
	Shared Ride	809,364	22.47	6.40	\$7.94	\$1.62	*NA*
	Taxi Ride	1,052,899	14.40	3.30	\$13.89	\$0.80	-905.91%
Downtown	Single Ride	2,881,576	15.29	4.41	\$10.48	\$3.19	-276.07%
	Shared Ride	370,734	22.34	6.09	\$7.55	\$1.49	*NA*
	Taxi Ride	744,709	12.47	2.53	\$11.81	\$0.62	-1725.41%
Suburbs	Single Ride	6,163,162	14.93	4.84	\$10.68	\$3.12	-109.25%
	Shared Ride	764,133	21.84	6.67	\$8.30	\$1.68	*NA*
	Taxi Ride	585,178	16.59	4.38	\$16.88	\$1.21	-475.59%

Notes: The table above summarizes ride-sharing and taxi activity in the analysis sample and is paneled across several dimensions. ΔN represents the percent change in average monthly ride-sharing after the beginning of the pandemic. Notice that the *Shared Ride* entries are blank because shared rides were no longer permitted after March 17th, 2020.

Figure A.2: Pandemic Trends

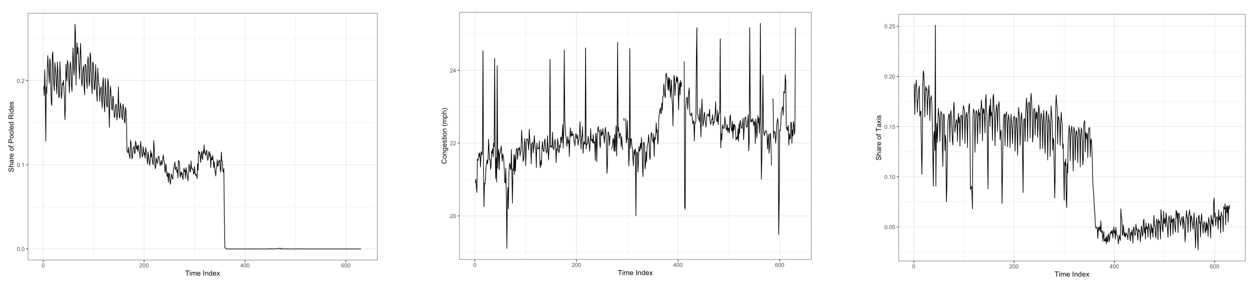


(a) Daily Cases

(b) Daily Deaths

Notes: The two figures above were generated from the Starschema data in Cook County, Illinois (where Chicago is located). The plot on the left shows a time-series of daily cases. The plot on the right shows a time-series of daily deaths.

Figure A.3: Pandemic Response Trends



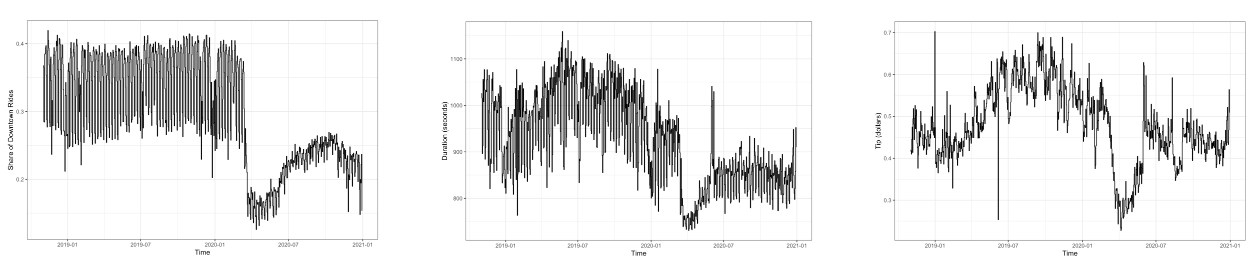
(a) Share of Pooled Rides

(b) Congestion (mph)

(c) Share of Taxis

Notes: The three figures above were generated from a sample of taxi and ride-sharing rides in Chicago. The leftmost plot shows the share of pooled rides. The middle plot shows congestion in terms of miles-per-hour. The rightmost plot shows the share of taxis.

Figure A.4: Trends in Ride-Sharing Characteristics



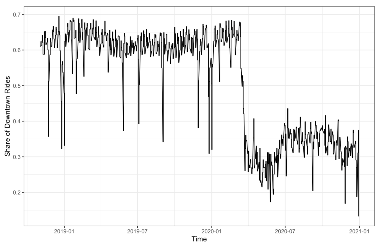
(a) Share of Downtown Rides

(b) Duration (seconds)

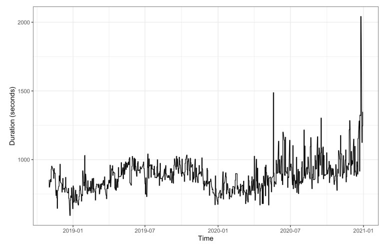
(c) Tip (dollars)

Notes: The three figures above were generated from a sample of ride-sharing rides in Chicago. The leftmost plot shows the share of downtown rides. The middle plot shows duration in terms of seconds. The rightmost plot shows tip in dollars.

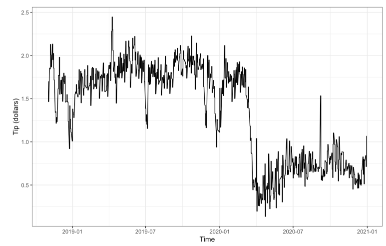
Figure A.5: Trends in Taxi Characteristics



(a) Share of Downtown Rides



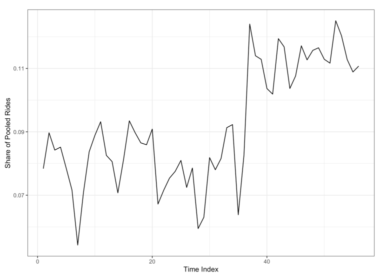
(b) Duration (seconds)



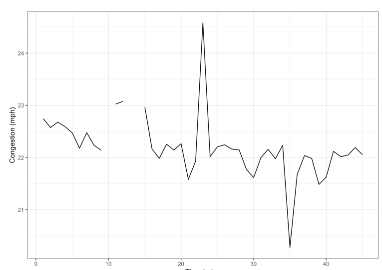
(c) Tip (dollars)

Notes: The three figures above were generated from a sample of taxi rides in Chicago. The leftmost plot shows the share of downtown rides. The middle plot shows duration in terms of seconds. The rightmost plot shows tip in dollars.

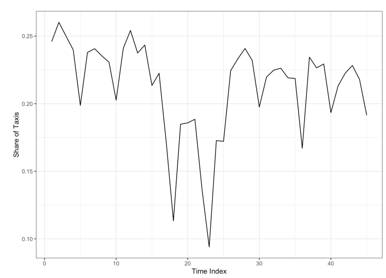
Figure A.6: Taxation Response Trends



(a) Share of Pooled Rides



(b) Congestion



(c) Share of Taxis

Notes: The three figures above were generated from a sample of taxi and ride-sharing rides in Chicago. The leftmost plot shows the share of pooled rides. The middle plot shows congestion in terms of miles-per-hour. The rightmost plot shows the share of taxis. The span of the time index is restricted to zoom in on the effect of the congestion tax.

A.4 Methodology

A.4.1 Regression Discontinuity with Local Regression

Regression discontinuity designs can be estimated with local linear regression using various kernels. The estimate can be computed in several steps.

$$(\hat{\alpha}_-(x), \hat{\beta}_-(x)) = \min_{\alpha,\beta} \sum_{i=1}^{n} \mathbf{1}[X_i < x](Y_i - \alpha - \beta(X_i - x))^2 K\left(\frac{X_i - x}{h}\right)$$
$$(\hat{\alpha}_+(x), \hat{\beta}_+(x)) = \min_{\alpha,\beta} \sum_{i=1}^{n} \mathbf{1}[X_i > x](Y_i - \alpha - \beta(X_i - x))^2 K\left(\frac{X_i - x}{h}\right)$$

The two estimates serve as a "left side" and a "right side" of the cutoff value c. The treatment $\hat{\tau}$ is estimated as

$$\hat{\tau} = \hat{\alpha}_+(c) - \hat{\alpha}_-(c)$$

where c is the cutoff value of interest. The kernel K can be any kernel. For the purposes of this study, I use a Gaussian, triangular, and rectangular kernel to check robustness.

A.4.2 Minimax Linear Estimator

Regression discontinuity designs that use linear regression and local linear regression with pre-specified kernels and bandwidths may suffer from partial identification problems because the running variable $\mathbf{X}$ is only observable over a discrete grid. The numerically derived minimax linear estimator from Imbens and Wager (2019) alleviates the partial identification problem by constructing bias-aware confidence intervals on the treatment effect. I will briefly describe the computation of this estimator.

Conditioning on smoothness of the estimator by restricting the second derivative of the function to some bound B allows for an estimate of the worst-case mean squared error. Local linear regression can be written as a linear estimator and we can optimize over the worst-case mean squared error:

$$\hat{\tau} = \sum_{i=1}^{n} \hat{\gamma}_i Y_i \qquad \hat{\gamma} = \min_{\gamma} \left\{ \sum_{i=1}^{n} \gamma_i^2 \text{Var}(Y_i(W_i)|X_i) + \mathbf{I}_B^2(\gamma) \right\}$$

$$\mathbf{I}_B(\gamma) = \sup_{\mu_0(\cdot), \mu_1(\cdot)} \left\{ \sum_{i=1}^{n} \gamma_i \mu_{W_i}(X_i) - (\mu_1(c) - \mu_0(c)) : |\mu''(x)| \leq B \; \forall w, x \right\}$$

The estimator does not rely on a specified kernel or bandwidth, meaning the only requirement is a value for the bound on the second derivative B. It also allows for the construction of bias-aware confidence intervals that account for bias.

B Appendix B

Impact of the Congestion Tax

B.1 Heterogeneity Analysis

Table B.1: Heterogeneity in the Effects of Chicago's Congestion Tax

	Dependent Variable								
	Shared Ride			Congestion			Taxi Rides		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Downtown Rides									
Treatment Effect	0.021*	0.045†	0.043†	-0.163*	1.248	-0.444	0.019*	0.015	0.031
	(0.008)	(0.015)	(0.010)	(0.066)	(0.892)	(0.415)	(0.008)	(0.026)	(0.011)
Suburban Rides									
Treatment Effect	0.012*	0.015*	0.026	-0.243†	1.242	-0.819	0.012†	0.011	0.017*
	(0.005)	(0.018)	(0.014)	(0.046)	(0.975)	(0.445)	(0.003)	(0.010)	(0.009)
Off-time Rides									
Treatment Effect	0.018	0.005	0.028	0.703†	0.115	0.109	0.008	0.033	0.026
	(0.012)	(0.006)	(0.009)	(0.059)	(0.363)	(0.300)	(0.014)	(0.017)	(0.006)
Type	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*
Day FE	Yes	No	No	Yes	No	No	Yes	No	No
Hour FE	Yes	No	No	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No	Yes	No	No

†p<0.01, *p<0.05

Notes: The results presented in this table show the effect of the congestion tax on shared rides, congestion, and taxi rides. Standard errors of OLS estimates are clustered at community areas as there is likely correlation of residuals.

B.2 Parametric Robustness Checks

Table B.2: Parametric Robustness of Tax Results

	Dependent Variable											
	Shared Ride				Congestion				Taxi Rides			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment Effect	0.021*	0.023†	0.021*	0.036†	-0.163*	-0.118	-0.044	-0.083	0.019*	0.020*	0.021†	0.019†
	(0.008)	(0.008)	(0.009)	(0.006)	(0.066)	(0.068)	(0.065)	(0.113)	(0.008)	(0.008)	(0.008)	(0.006)
Observations	28k	28k	28k	28k	23k	23k	23k	23k	23k	23k	23k	23k
Hour FE	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Day FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Location FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No

†p<0.01, *p<0.05

Notes: The results presented in this table show robustness of parametric estimates on shared rides, congestion, and taxi rides in the tax analysis. Standard errors of estimates with location fixed effects are clustered at community areas as there is likely correlation of residuals.

B.3 Non-Parametric Robustness Checks

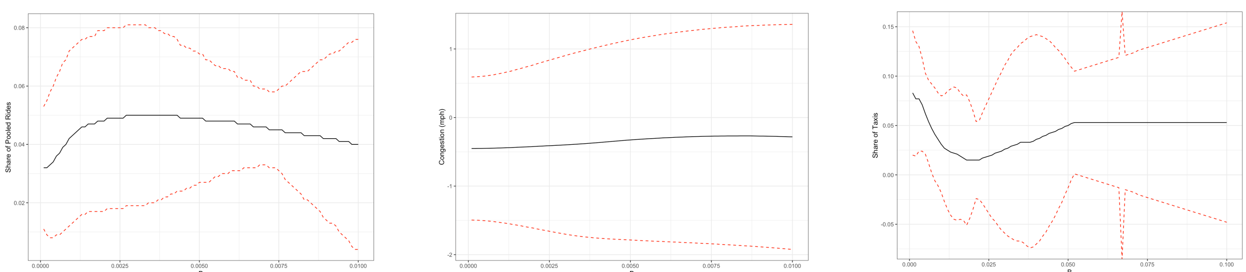
Table B.3: Non-Parametric Robustness of Tax Results

	Dependent Variable											
	Shared Ride				Congestion				Taxi Rides			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Triangular	$0.021^{\dagger}$	$0.045^{\dagger}$	$0.047^{\dagger}$	$0.041^{\dagger}$	$-0.156^{\dagger}$	1.248	-0.047	-0.426	$0.053^{\dagger}$	0.015	$0.056^{\dagger}$	$0.078^{\dagger}$
	(0.002)	(0.015)	(0.012)	(0.010)	(0.017)	(0.892)	(0.520)	(0.611)	(0.000)	(0.026)	(0.020)	(0.024)
Gaussian	$0.041^{\dagger}$	$0.035^{\dagger}$	$0.032^{\dagger}$	$0.033^{\dagger}$	-0.308	-0.451	-0.405	-0.374	$0.072^{\dagger}$	$0.082^{\dagger}$	$0.092^{\dagger}$	0.093†
	(0.008)	(0.009)	(0.008)	(0.007)	(0.462)	(0.596)	(0.594)	(0.525)	(0.018)	(0.022)	(0.022)	(0.019)
Epanechnikov	$0.021^{\dagger}$	$0.047^{\dagger}$	$0.047^{\dagger}$	$0.039^{\dagger}$	$-0.159^{\dagger}$	1.404	-0.206	-0.551	$0.053^{\dagger}$	0.012	$0.063^{\dagger}$	$0.084^{\dagger}$
	(0.003)	(0.017)	(0.013)	(0.010)	(0.022)	(0.976)	(0.619)	(0.724)	(0.000)	(0.028)	(0.024)	(0.027)
Observations	56	56	56	56	45	45	45	45	45	45	45	45
Bandwidth	3	4	6	8	3	4	6	8	3	4	6	8

†p<0.01, *p<0.05

Notes: The results presented in this table show robustness of non-parametric estimates on shared rides, congestion, and taxi rides in the tax analysis. The shared ride and congestion models are fit on ride-sharing data excluding taxis.

Figure B.1: Minimax Robustness of Tax Results



(a) Share of Pooled Rides (b) Congestion (c) Share of Taxis

Notes: The three figures above were generated from a sample of taxi and ride-sharing rides in Chicago. The leftmost plot shows the minimax estimate on share of pooled rides. The middle plot shows the minimax estimate on congestion in terms of miles-per-hour. The rightmost plot shows the minimax estimate on the share of taxis. The red dotted lines are bias-aware confidence intervals.

C Appendix C

Impact of the Pandemic

C.1 Heterogeneity Analysis

Table C.1: Heterogeneity in the Effects of the Pandemic

	Dependent Variable								
	Shared Ride			Congestion			Taxi Rides		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
All Rides									
Treatment Effect	-0.085†	-0.056†	-0.067†	0.461†	0.513†	1.312†	-0.018†	-0.053†	-0.077†
	(0.005)	(0.013)	(0.010)	(0.071)	(0.117)	(0.108)	(0.005)	(0.008)	(0.006)
Downtown Rides									
Treatment Effect	-0.095†	-0.023*	-0.066†	0.552†	0.731*	1.106†	-0.033*	-0.023*	-0.112†
	(0.011)	(0.010)	(0.010)	(0.077)	(0.295)	(0.091)	(0.013)	(0.011)	(0.009)
Suburban Rides									
Treatment Effect	-0.082†	-0.018	-0.067*	0.545†	0.219	1.482	-0.012†	-0.002	-0.030*
	(0.005)	(0.013)	(0.010)	(0.064)	(0.135)	(0.118)	(0.003)	(0.001)	(0.004)
Weekend Rides									
Treatment Effect	-0.070†	-0.036	-0.070†	0.378†	0.385	1.004†	-0.010†	-0.012	-0.028†
	(0.005)	(0.027)	(0.009)	(0.070)	(0.352)	(0.173)	(0.003)	(0.006)	(0.004)
Weekday Rides									
Treatment Effect	-0.066†	-0.037	-0.011*	0.541†	0.314	1.312	-0.016†	-0.015*	-0.077†
	(0.004)	(0.022)	(0.007)	(0.062)	(0.166)	(0.108)	(0.004)	(0.006)	(0.006)
Off-time Rides									
Treatment Effect	0.044†	0.000	0.000	0.565†	0.492	1.306	-0.016†	-0.021†	-0.087*
	(0.003)	(0.000)	(0.000)	(0.063)	(0.264)	(0.103)	(0.005)	(0.005)	(0.007)
Rush-hour Rides									
Treatment Effect	-0.083†	-0.012	-0.063*	0.517†	0.024	1.386	-0.015†	-0.003	-0.057
	(0.006)	(0.012)	(0.010)	(0.063)	(0.169)	(0.118)	(0.004)	(0.006)	(0.005)
Type	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*
Day FE	Yes	No	No	Yes	No	No	Yes	No	No
Hour FE	Yes	No	No	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No	Yes	No	No
Pandemic Control	Yes	No	No	Yes	No	No	Yes	No	No

†p<0.01, *p<0.05

Notes: The results presented in this table show the effect of the pandemic on shared rides, congestion, and taxi rides. Standard errors of OLS estimates are clustered at community areas as there is likely correlation of residuals.

Table C.2: Heterogeneity in Effects of the Pandemic on Taxi Ride Characteristics

	Dependent Variable								
	Downtown Share			Duration			Tip		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rush-hour Rides									
Treatment Effect	0.008	0.015	0.021	-65.210*	-70.363	-42.770	0.047	-0.142	-0.094
	(0.007)	(0.015)	(0.014)	(29.451)	(37.965)	(20.574)	(0.037)	(0.091)	(0.063)
Off-time Rides									
Treatment Effect	0.005	0.002	0.000	-61.287	-67.035	-52.520	0.117	-0.004	0.054
	(0.008)	(0.024)	(0.021)	(39.987)	(48.292)	(23.761)	(0.095)	(0.134)	(0.080)
Type	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*
Day FE	Yes	No	No	Yes	No	No	Yes	No	No
Hour FE	Yes	No	No	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No	Yes	No	No
Pandemic Control	Yes	No	No	Yes	No	No	Yes	No	No

$^{\dagger}p<0.01$, $^{*}p<0.05$

Notes: The results presented in this table show the effect of the pandemic on downtown rides, duration, and tip. Standard errors of OLS estimates are clustered at community areas as there is likely correlation of residuals.

Table C.3: Heterogeneity in Effects of the Pandemic on Ride-Sharing Ride Characteristics

	Dependent Variable								
	Downtown Share			Duration			Tip		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rush-hour Rides									
Treatment Effect	-0.062†	-0.115†	-0.119	-144.511†	-75.677†	-177.124†	-0.048†	-0.014	-0.039*
	(0.006)	(0.019)	(0.019)	(11.641)	(29.554)	(12.862)	(0.017)	(0.013)	(0.012)
Off-time Rides									
Treatment Effect	-0.028†	-0.082†	-0.080*	-68.351†	-42.113†	-75.011†	-0.042†	-0.054†	-0.071†
	(0.003)	(0.013)	(0.013)	(5.456)	(12.767)	(6.889)	(0.009)	(0.019)	(0.018)
Weekday Rides									
Treatment Effect	-0.043†	-0.100†	-0.104*	-105.577†	-64.651†	-135.498†	-0.047†	-0.033*	-0.051*
	(0.004)	(0.017)	(0.017)	(8.157)	(21.931)	(9.723)	(0.013)	(0.013)	(0.013)
Weekend Rides									
Treatment Effect	-0.034†	-0.041†	-0.028*	-74.144†	-14.085	-54.493†	-0.035†	-0.068†	-0.115
	(0.003)	(0.014)	(0.010)	(6.565)	(26.214)	(15.397)	(0.010)	(0.023)	(0.023)
Type	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*	*OLS*	*Local*	*Minimax*
Day FE	Yes	No	No	Yes	No	No	Yes	No	No
Hour FE	Yes	No	No	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No	Yes	No	No
Pandemic Control	Yes	No	No	Yes	No	No	Yes	No	No

$^{\dagger}p<0.01$, $^{*}p<0.05$

Notes: The results presented in this table show the effect of the pandemic on downtown rides, duration, and tip. Standard errors of OLS estimates are clustered at community areas as there is likely correlation of residuals.

C.2 Parametric Robustness Checks

Table C.4: Parametric Robustness of Pandemic Results

	Dependent Variable											
	Shared Ride				Congestion				Taxi Rides			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Including COVID-19 Case Control												
Treatment Effect	-0.085†	-0.084†	-0.084†	-0.082†	0.541†	0.447†	0.445†	0.436†	-0.016†	-0.015†	-0.015†	-0.016†
	(0.005)	(0.005)	(0.005)	(0.001)	(0.062)	(0.058)	(0.058)	(0.018)	(0.004)	(0.004)	(0.004)	(0.001)
Excluding COVID-19 Case Control												
Treatment Effect	-0.084†			-0.081†	0.547†			0.449†	-0.015†			-0.015†
	(0.005)			(0.001)	(0.061)			(0.018)	(0.004)			(0.001)
Observations	1.20M	1.20M	1.20M	1.20M	849k	849k	849k	849k	849k	849k	849k	849k
Hour FE	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Day FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Location FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No

†p<0.01, *p<0.05

Notes: The results presented in this table show robustness of parametric estimates on shared rides, congestion, and taxi rides in the pandemic analysis. Standard errors of estimates with location fixed effects are clustered at community areas as there is likely correlation of residuals. "COVID-19 Case Control" refers to an additional controlling variable for daily COVID-19 cases.

Table C.5: Parametric Robustness of Pandemic Taxi Characteristics Results

	Dependent Variable											
	Downtown Share				Duration				Tip			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Including COVID-19 Case Control												
Treatment Effect	0.008	0.007	0.007	-0.005	-61.06*	-64.30*	-64.63*	-48.95*	0.078	0.082	0.082	0.124†
	(0.006)	(0.006)	(0.006)	(0.005)	(24.31)	(24.85)	(25.01)	(23.49)	(0.052)	(0.050)	(0.051)	(0.029)
Excluding COVID-19 Case Control												
Treatment Effect	0.007			-0.006	-64.97†			-53.11*	0.076			0.117†
	(0.006)			(0.005)	(24.55)			(23.46)	(0.052)			(0.029)
Observations	152k	152k	152k	152k	152k	152k	152k	152k	152k	152k	152k	152k
Hour FE	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Day FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Location FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No

†p<0.01, *p<0.05

Notes: The results presented in this table show robustness of parametric estimates on shared rides, congestion, and taxi rides in the pandemic analysis. Standard errors of estimates with location fixed effects are clustered at community areas as there is likely correlation of residuals. "COVID-19 Case Control" refers to an additional controlling variable for daily COVID-19 cases.

Table C.6: Parametric Robustness of Pandemic Ride-Sharing Characteristics Results

	Dependent Variable											
	Downtown Share				Duration				Tip			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Including COVID-19 Case Control												
Treatment Effect	-0.040†	-0.040†	-0.041†	-0.034†	-96.15†	-93.29†	-95.31†	-106.30†	-0.044†	-0.045†	-0.045†	-0.064†
	(0.003)	(0.003)	(0.003)	(0.001)	(7.165)	(6.58)	(6.69)	(2.28)	(0.011)	(0.010)	(0.010)	(0.004)
Excluding COVID-19 Case Control												
Treatment Effect	-0.041†			-0.035†	-102.06†			-111.88†	-0.047†			-0.067†
	(0.003)			(0.001)	(7.26)			(2.27)	(0.010)			(0.004)
Observations	1.01M	1.01M	1.01M	1.01M	1.01M	1.01M	1.01M	1.01M	1.01M	1.01M	1.01M	1.01M
Hour FE	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Day FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Location FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No

†p<0.01, *p<0.05

Notes: The results presented in this table show robustness of parametric estimates on shared rides, congestion, and taxi rides in the pandemic analysis. Standard errors of estimates with location fixed effects are clustered at community areas as there is likely correlation of residuals. "COVID-19 Case Control" refers to an additional controlling variable for daily COVID-19 cases.

C.3 Non-Parametric Robustness Checks

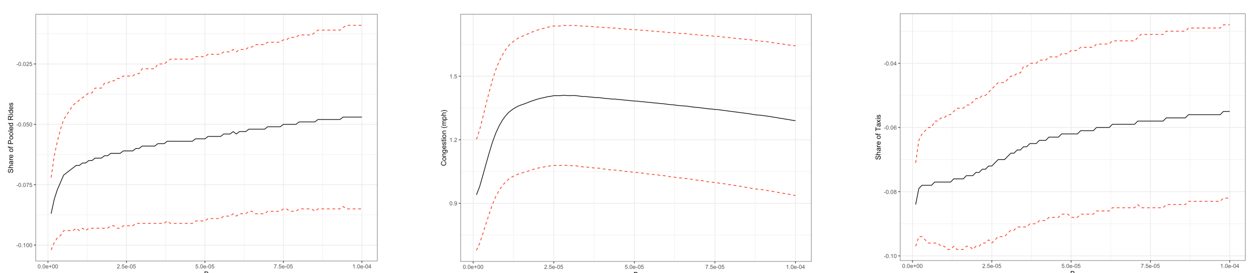
Table C.7: Non-Parametric Robustness of Pandemic Results

	Dependent Variable											
	Shared Ride				Congestion				Taxi Rides			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Standard Regression Discontinuity												
Triangular	-0.020	-0.028*	-0.056†	-0.068†	0.227	0.185	0.513†	0.884†	-0.023†	-0.031†	-0.053†	-0.073†
	(0.016)	(0.014)	(0.013)	(0.010)	(0.124)	(0.122)	(0.117)	(0.129)	(0.006)	(0.007)	(0.008)	(0.007)
Gaussian	-0.051†	-0.060†	-0.074†	-0.089†	0.449†	0.595†	1.101†	1.400†	-0.050†	-0.059†	-0.077†	-0.080†
	(0.013)	(0.012)	(0.008)	(0.005)	(0.107)	(0.111)	(0.118)	(0.116)	(0.008)	(0.008)	(0.006)	(0.004)
Epanechnikov	-0.022	-0.031*	-0.060†	-0.070†	0.200	0.180	0.560†	0.958†	-0.025†	-0.034†	-0.056†	-0.077†
	(0.016)	(0.014)	(0.013)	(0.009)	(0.132)	(0.126)	(0.124)	(0.134)	(0.007)	(0.007)	(0.008)	(0.007)
Additional Covariate (Daily COVID-19 Cases)												
Triangular	-0.026	-0.028*	-0.053†	-0.068†	-1.360	-0.830	-0.350	-0.026	0.035	0.025	0.009	-0.002
	(0.013)	(0.013)	(0.014)	(0.010)	(1.094)	(0.840)	(0.606)	(0.418)	(0.032)	(0.024)	(0.018)	(0.013)
Gaussian	-0.047†	-0.059†	-0.073†	-0.082†	-0.352	-0.207	0.119	0.154	0.010	0.006	-0.003	-0.004
	(0.013)	(0.012)	(0.009)	(0.007)	(0.623)	(0.538)	(0.349)	(0.243)	(0.018)	(0.015)	(0.011)	(0.008)
Epanechnikov	-0.027	-0.030*	-0.058†	-0.070†	-1.212	-0.695	-0.301	0.021	0.033	0.022	0.007	-0.005
	(0.014)	(0.014)	(0.014)	(0.009)	(1.077)	(0.843)	(0.594)	(0.397)	(0.032)	(0.024)	(0.017)	(0.013)
Observations	883	883	883	883	631	631	631	631	631	631	631	631
Bandwidth	10	14	30	60	10	14	30	60	10	14	30	60

†p<0.01, *p<0.05

Notes: The results presented in this table show robustness of non-parametric estimates on shared rides, congestion, and taxi rides in the pandemic analysis. The shared ride and congestion models are fit on ride-sharing data excluding taxis.

Figure C.1: Minimax Robustness of Pandemic Results



(a) Share of Pooled Rides (b) Congestion (c) Share of Taxis

Notes: The three figures above were generated from a sample of taxi and ride-sharing rides in Chicago. The leftmost plot shows the minimax estimate on share of pooled rides. The middle plot shows the minimax estimate on congestion in terms of miles-per-hour. The rightmost plot shows the minimax estimate on the share of taxis. The red dotted lines are bias-aware confidence intervals.

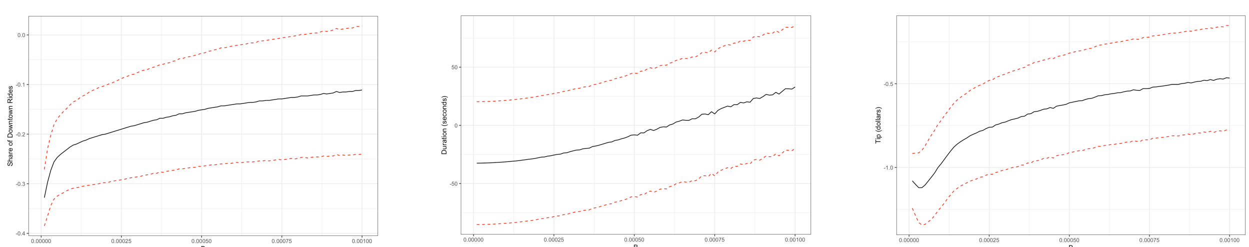
Table C.8: Non-Parametric Robustness of Pandemic Taxi Characteristics Results

	Dependent Variable											
	Downtown Share				Duration				Tip			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Standard Regression Discontinuity												
Triangular	-0.057	-0.090*	-0.200†	-0.267†	-43.18	-11.90	58.15	17.41	-0.160	-0.229*	-0.516†	-0.895†
	(0.050)	(0.042)	(0.036)	(0.027)	(62.86)	(50.38)	(38.49)	(29.35)	(0.146)	(0.116)	(0.109)	(0.103)
Gaussian	-0.182†	-0.220†	-0.305†	-0.341†	44.81	50.37	16.31	68.33†	-0.459†	-0.636†	-1.046†	-1.101†
	(0.035)	(0.033)	(0.024)	(0.015)	(37.51)	(34.09)	(25.13)	(19.76)	(0.103)	(0.106)	(0.094)	(0.060)
Epanechnikov	-0.058	-0.098*	-0.215†	-0.279†	-48.23	-5.87	67.15	9.73	-0.195	-0.253*	-0.565†	-0.957†
	(0.048)	(0.040)	(0.035)	(0.026)	(63.61)	(50.67)	(39.09)	(29.43)	(0.145)	(0.111)	(0.109)	(0.100)
Additional Covariate (Daily COVID-19 Cases)												
Triangular	-0.058	-0.089*	-0.186†	-0.251†	-44.36	-12.17	50.51	40.61	-0.162	-0.238*	-0.526†	-0.868†
	(0.051)	(0.044)	(0.039)	(0.029)	(65.74)	(51.88)	(37.57)	(30.59)	(0.148)	(0.116)	(0.115)	(0.112)
Gaussian	-0.169†	-0.205†	-0.272†	-0.306†	39.78	46.73	41.90	92.70†	-0.467†	-0.638†	-0.980†	-1.023†
	(0.037)	(0.035)	(0.026)	(0.016)	(37.24)	(33.16)	(28.68)	(30.84)	(0.107)	(0.112)	(0.106)	(0.066)
Epanechnikov	-0.058	-0.097*	-0.199†	-0.262†	-49.71	-5.57	58.75	38.84	-0.197	-0.263*	-0.579†	-0.929†
	(0.050)	(0.042)	(0.037)	(0.028)	(66.62)	(52.16)	(37.65)	(30.84)	(0.148)	(0.112)	(0.114)	(0.010)
Observations	567	567	567	567	567	567	567	567	567	567	567	567
Bandwidth	10	14	30	60	10	14	30	60	10	14	30	60

†p<0.01, *p<0.05

Notes: The results presented in this table show robustness of non-parametric estimates on the share of downtown rides, duration in seconds, and tip in dollars in the pandemic analysis for taxi rides.

Figure C.2: Minimax Robustness of Pandemic Ride-Share Characteristics Results



(a) Share of Downtown Rides (b) Duration (seconds) (c) Tip (dollars)

Notes: The three figures above were generated from a sample of taxi rides in Chicago. The leftmost plot shows the minimax estimate on share of downtown rides. The middle plot shows the minimax estimate on duration in seconds. The rightmost plot shows the minimax estimate on the tip in dollars. The red dotted lines are bias-aware confidence intervals.

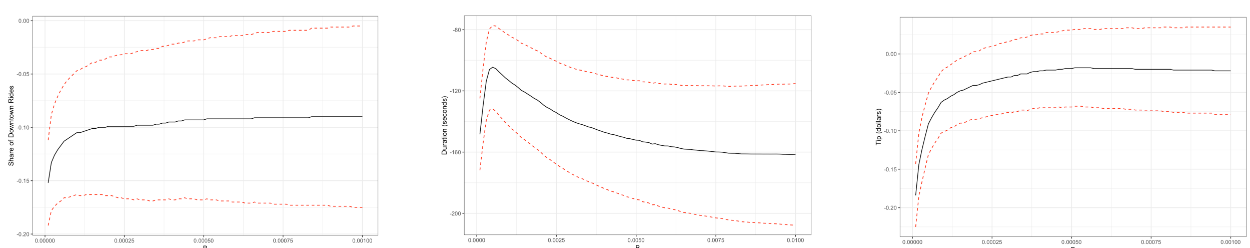
Table C.9: Non-Parametric Robustness of Pandemic Ride-Sharing Characteristics Results

	Dependent Variable											
	Downtown Share				Duration				Tip			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Standard Regression Discontinuity												
Triangular	-0.102†	-0.087†	-0.104†	-0.130†	-13.57	-10.70	-59.85†	-120.86†	-0.018	-0.020	-0.046†	-0.131†
	(0.037)	(0.027)	(0.020)	(0.016)	(22.07)	(21.07)	(21.85)	(20.21)	(0.020)	(0.017)	(0.013)	(0.017)
Gaussian	-0.101†	-0.110†	-0.146†	-0.174†	-47.62*	-76.84†	-142.78†	-142.54†	-0.038†	-0.066†	-0.166†	-0.195†
	(0.020)	(0.018)	(0.015)	(0.011)	(20.17)	(20.96)	(17.91)	(11.67)	(0.012)	(0.013)	(0.016)	(0.012)
Epanechnikov	-0.100†	-0.084†	-0.106†	-0.135†	-10.63	-10.84	-68.51†	-131.09†	-0.018	-0.020	-0.053†	-0.148†
	(0.037)	(0.027)	(0.021)	(0.016)	(22.98)	(22.95)	(22.95)	(19.77)	(0.020)	(0.017)	(0.013)	(0.018)
Additional Covariate (Daily COVID-19 Cases)												
Triangular	-0.118†	-0.096†	-0.104†	-0.131†	-13.10	-10.04	-56.83†	-117.74†	-0.018	-0.018	-0.041†	-0.124†
	(0.032)	(0.025)	(0.020)	(0.016)	(23.01)	(21.30)	(21.60)	(20.69)	(0.020)	(0.017)	(0.013)	(0.017)
Gaussian	-0.102†	-0.112†	-0.141†	-0.151†	-45.08	-72.55†	-133.92†	-140.12†	-0.033†	-0.059†	-0.142†	-0.157†
	(0.020)	(0.018)	(0.015)	(0.012)	(19.64)	(20.73)	(18.34)	(12.60)	(0.012)	(0.012)	(0.016)	(0.013)
Epanechnikov	-0.116†	-0.092†	-0.107†	-0.136†	-10.36	-10.13	65.25†	-128.82†	-0.018	-0.019	-0.047†	-0.140†
	(0.033)	(0.026)	(0.021)	(0.016)	(23.90)	(23.17)	(22.80)	(20.32)	(0.020)	(0.017)	(0.013)	(0.018)
Observations	793	793	793	793	793	793	793	793	793	793	793	793
Bandwidth	10	14	30	60	10	14	30	60	10	14	30	60

$^{\dagger}p<0.01$, $^{*}p<0.05$

Notes: The results presented in this table show robustness of non-parametric estimates on the share of downtown rides, duration in seconds, and tip in dollars in the pandemic analysis for ride-sharing rides.

Figure C.3: Minimax Robustness of Pandemic Ride-Sharing Characteristics Results



(a) Share of Downtown Rides

(b) Duration (seconds)

(c) Tip (dollars)

Notes: The three figures above were generated from a sample of ride-sharing rides in Chicago. The leftmost plot shows the minimax estimate on share of downtown rides. The middle plot shows the minimax estimate on duration in seconds. The rightmost plot shows the minimax estimate on the tip in dollars. The red dotted lines are bias-aware confidence intervals.