Should Cities Tax Uber and Lyft?

Matthew Tarduno

December 2022

PRELIMINARY AND INCOMPLETE; PLEASE DO NOT CITE OR DISTRIBUTE

Abstract

This paper evaluates three first-order concerns facing cities as they decide how and whether to tax ridesharing companies: (1) the effectiveness of ridesharing taxes at addressing traffic congestion, (2) the distributional burden of these taxes, and (3) the efficiency with which ridesharing taxes collects income. I first use data from Chicago to show that the demand for ridesharing is highly inelastic both in gross terms ($\epsilon^D = -0.15$), and relative to the elasticity of supply ($\epsilon^S = -0.96$). As a result, taxing Uber and Lyft does little to alleviate traffic congestion or air pollution. The point estimates from Difference-in-differences specifications suggest coincident increases in pollution and congestion in Chicago following these taxes, and can reject improvements in air pollution and traffic larger than 5% and 3%, respectively. This inelasticity, however, also means that taxing ridesharing is likely an efficient way for local governments to collect funds, especially when contrasted against other common revenue sources. Lastly, the inelasticity of ridesharing demand implies that most of the tax burden (roughly 86% in Chicago) falls on riders. Survey data suggests that high-income individuals bear most of the costs of a ridesharing tax, even as a fraction of income. For reference, the implied distribution of ridesharing tax burdens is roughly as progressive as the federal income tax schedule. In sum, taxing ridesharing appears an attractive tool for local governments from equity and efficiency standpoints, but should not be expected to lead to significant reductions in traffic externalities.

1. Introduction

Why do we tax some goods and not others? Governments typically impose taxes either as a source of revenue, or to discourage behavior that is deemed harmful to individuals (internalities) or society (externalities). In some settings, vertical equity norms lead policymakers or legislators to avoid or redesign taxes that place an undue burden on low-income individuals.

For each of these considerations, public economics provides guidance for whether and how to tax certain goods. A strand of the public economics literature dating back to Ramsey (1927) characterizes the efficiency with which various taxes raise government revenue. A second branch of public economics follows Pigou in determining optimal externality taxes, and the implied welfare gains. Lastly, canonical models of tax incidence provide insight into who bears the burden of a tax, which then informs discussions of whether or not a tax is progressive (Kotlikoff and Summers, 1987; Fullerton and Metcalf, 2002).

Over the past decade, many governments have moved to tax trips provided by companies like Uber and Lyft[1], typically citing congestion and lost parking and registration revenue as motivation. Little evidence, however, exists on how riders, drivers, and ridesharing companies respond to these taxes. As such, it is unclear how ridesharing taxes perform along efficiency, equity, or externality dimensions. To that end, this paper attempts to answer the following three questions: (i) Do ridesharing taxes reduce externalities? (ii) Are ridesharing taxes an efficient (low excess burden) source of government revenue? (iii) Are ridesharing taxes progressive?

To answer these research questions, I use the imposition of ridesharing taxes in Chicago and Washington DC to study responses in prices and quantities in these markets, as well as estimate the impacts of these policies on externalities. I also draw on data from the National Household Travel Survey and the Consumer Expenditure Survey to understand how the burden of ridesharing taxes would differ across income groups, as well as traffic data to understand whether the tax impacted traffic congestion.

I find that ridesharing is inelastic with respect to taxation: for every 1% increase in prices induced by the policy, rides decreased by roughly 0.15%. Accordingly, I estimate that most of the tax (86%) is passed on to consumers. This inelasticity makes ridesharing attractive from a Ramsey tax perspective, especially given that other revenue sources for local governments (e.g., sales taxes or sin taxes) can be quite elastic. Conversely, the inelastic demand for Uber and Lyft suggests that ridesharing taxes would generate little welfare via reduced congestion externalities. Using two different traffic datasets, I estimate that traffic speeds inside Chicago's Surcharge Zone increased by roughly 0.8 to 3% following the imposition of these taxes. I can reject with 95% confidence increases in traffic speeds of more than 3%. In the final section of the paper, I demonstrate that under the elasticities estimated above, ridesharing taxes are progressive. On average, high-income households take many more ridesharing trips than do low-income households. Low-income passengers would pay less in taxes that would high-income households, even as a fraction of income. For reference, the implied progressivity of ridesharing taxes is similar to the progressivity of the Federal income tax schedule (including EITC transfers).

2. Relation to the Literature

This paper is related to a number of reduced-form papers that use observational data to estimate the impact of Uber and Lyft on urban externalities.

Several papers demonstrate a causal association between traffic congestion and ridesharing activity. Tarduno (2021) finds that the exit of Uber and Lyft from Austin, TX led to an increase in traffic speeds. Using traffic and TNC data from San Francisco, Erhardt, Roy, Cooper, Sana, Chen, and Castiglione (2019) estimate that

[1] For example, New York, Mexico City, San Francisco, Chicago, and Washington DC all tax ridesharing trips.

ridesharing increased vehicle delays relative to simulations of traffic in the absence of ridesharing.

Regarding air pollution, simulations by Ward, Michalek, and Samaras (2021) suggest that replacing a personal vehicle trip with a ridesharing trip reduces local air pollution (due to a reduction in cold starts) but increases GHG emissions. Leveraging Uber's staggered rollout, Sarmiento and Kim (2021) conclude that Uber improves air pollution, largely driven by reductions in ozone during the summer. Krishnamurthy, Ngo et al. (2022) conclude that Uber entry in California decreased air pollution on average, but this heterogeneity masks increases in peak-hour air pollution following Uber and Lyft entry.

If ridesharing entry causes congestion to increase, or pollution to decrease, there are several reasons why taxing ridesharing may not cause the opposite effect. First, changes in ridesharing activity at the margin may have different impacts than ridesharing activity on average. Second, if ridesharing demand is highly inelastic, it is not clear that these policies will impact congestion or pollution, even if these companies had a detectable impact on these outcomes when they entered the city. Third, if ridesharing taxes do generate significant demand responses, it is important to understand whether there are spillover effects.

Several existing papers shed light on the demand and supply elasticities of Uber and Lyft. Cohen, Hahn, Hall, Levitt, and Metcalfe (2016) use price cutoffs in Uber's surge pricing algorithm to estimate the demand curve for Uber, and generally report that riders are inelastic (with elasticities between -0.6 and -0.4). An RCT in Cairo conducted by Christensen and Osman (2021) yielded larger elasticity estimates (-0.84). Estimates of supply elasticities are substantially higher than estimates of demand elasticities: Chen, Rossi, Chevalier, and Oehlsen (2019) report a median supply elasticity 1.92 for US Uber drivers. Using variation in leased Uber vehicles, Angrist, Caldwell, and Hall (2021) estimate an intertemporal elasticity of 1.2. Taken at face value, these papers suggest that the demand for ridesharing is more inelastic than the supply, implying that riders will bear the majority of the tax burden. Importantly, however, the literature has yet to estimate demand and supply elasticities simultaneously. This is important because estimates of elasticities may depend on the salience of the price change, and the time horizon over which decisions are made. This paper contributes to this literature by estimating the policy-relevant elasticities and pass-through of Uber and Lyft taxes.

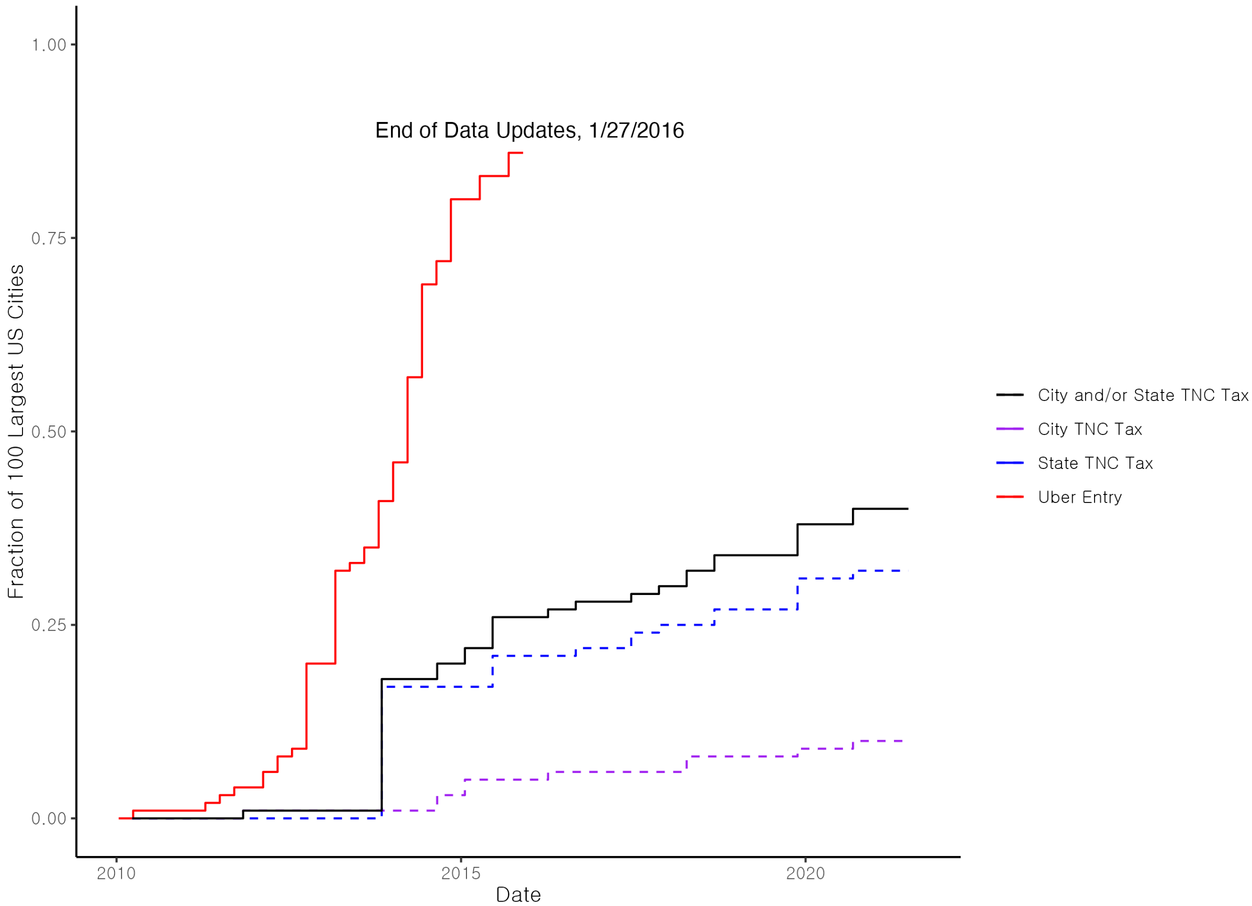
Lastly, the role of ridesharing vis-a-vis public transportation is an area of active research. Several papers find that ridesharing is a complement to public transit, most notably Hall, Palsson, and Price (2018). Following this notion, cities have implemented or are piloting programs to subsidize ridesharing trips to public transit stops. In the discussion section of this paper, I discuss the conditions under which this complementarity does and does not carry implications for taxing Uber and Lyft.

3. Ridesharing Taxes in the United States

After Uber was founded in 2009, ridesharing quickly expanded to cover the majority of large US cities. Data collected by Forbes shows that Uber was active in at least 85 of the 100 largest US cities by February of 2016. Following the expansion of TNCs, there has been a consistent increase in policies aimed at taxing ridesharing. As of 2022, ridesharing is subject to specific taxation (ad valorem or per-trip) in just under 50 of the 100 largest US cities (see Figure 1).

There is significant variation in geographic coverage and states policy goals. Several states impose taxes on ridesharing: Alabama, California, Georgia, Hawaii, Iowa, Massachusetts, Nevada, New Jersey, New York State, Ohio, Rhode Island, South Carolina, South Dakota, and Wyoming. The majority of state-level taxes are ad valorem. City-level taxes are more often levied on a per-trip basis. Notable city-level ridesharing taxes include New York City (2012), Chicago (2020), San Francisco (2020), Philadelphia (2016), and Washington DC (2018). For an overview of the attributes of different state- and city-level ridesharing taxes in the US, see Lehe, Devunuri, Rondan, and Pandey (2021).

Figure 1 — TNC Entry and Taxation in the 100 Largest US Cities



This Figure plots the expansion of Uber and ridesharing taxes in the 100 largest US cities. The red line plots the fraction of cities where Uber is active, according to data compiled by Forbes and published in January 2016. The black line represents the fraction of the 100 largest US cities where ridesharing is exposed to a specific (ad valorem or per-trip) tax. The purple and blue lines decompose this into city and State-level taxes, respectively.

In this paper I focus on the imposition of Chicago's ridesharing tax. The city of Chicago publishes detailed data on ridesharing in the city, which allows for a more complete characterization of the impact of these policies than is possible in other areas. I also investigate traffic and air pollution outcomes in Washington DC, which imposed a ridesharing tax in late 2018.

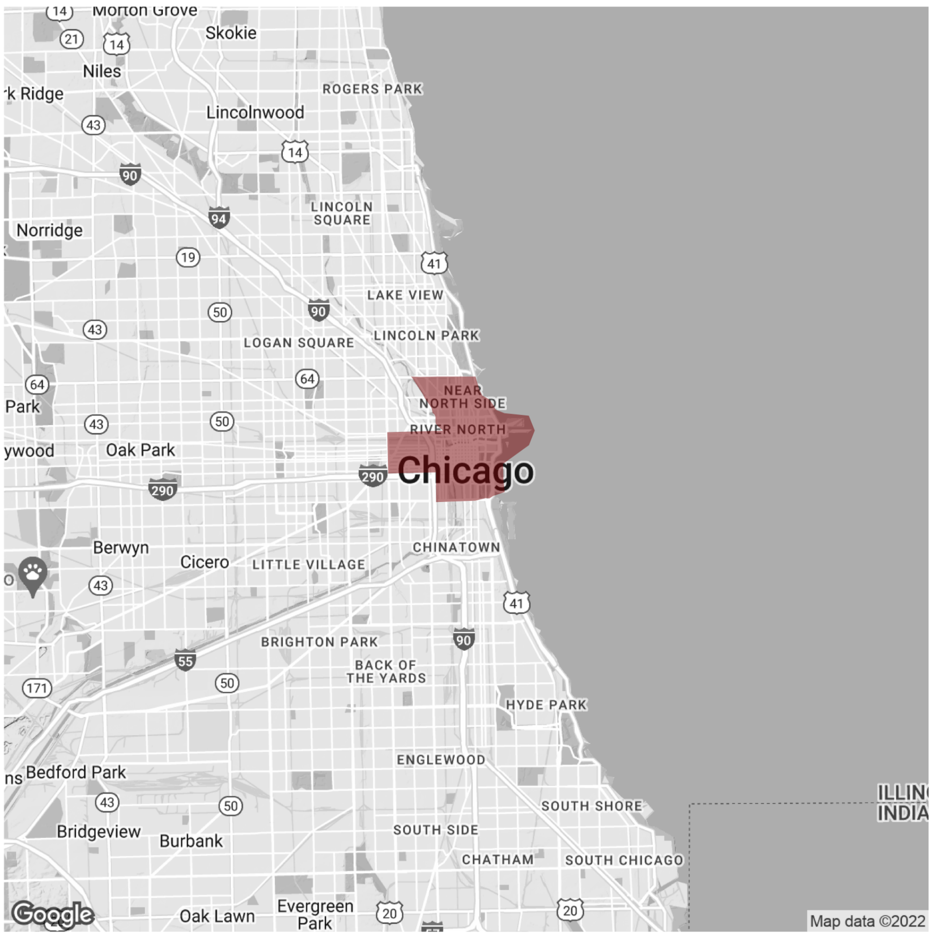
3.1. Chicago's Ground Transportation Tax

Starting in 2015, Chicago imposed a flat fee of \$0.30 on all ridesharing trips originating or ending in the city. This fee was increased to 52 cents in 2016, and again to 72 cents in 2019.

On January 6$^{\text{th}}$, 2020, the city's flat ridesharing fee was replaced with the *Ground Transportation Tax* (GTT), which varied by trip time and location, and whether the trip was shared or private. Private trips that either started or ended in the downtown zone (plotted in Figure 2) during peak hours (henceforth "Downtown Surcharge" trips) were charged \$3.00; private trips without the Downtown Surcharge were changed \$1.25. Shared trips were charged \$1.25 and \$0.65 with and without the Downtown Surcharge, respectively. Additionally, trips to and from "Special Zones" (Airports, Navy Pier, and McCormick Place) were charged additional fees.[2] These fees are detailed in Table 1.

The stated goal of the GTT was to reduce congestion and air pollution, with revenue earmarked for public transit investments and transportation accessibility initiatives (Mayor's Press Office, 2019).[3] Equity was also a central topic of discussion when the new tax structure was announced: The office of Mayor Lightfoot claimed that the new fee schedule would advance equity, but other community members — most notably a group of 30 Ministers from South and West Chicago — questioned this claim. Uber also proposed an alternative tax structure that it claimed would perform better on equity grounds (Uber, 2019). This proposal also was supported by Lyft, but ultimately rejected by the city government.

Figure 2 — Chicago's Downtown Surcharge Zone



This map shows Chicago's Downtown Surcharge Zone. Both private and shared trips are charged additional fees if the trip starts or ends within the Zone during peak hours (weekdays 6 am to 10 pm).

[2]The Special Zone fees were $8.00 for private trips that also used the Downtown Surcharge Zone during peak hours; $6.25 for private trips that did not use the Downtown Surcharge Zone, or did not occur during peak hours; $6.25 for pooled trips that used the Downtown Surcharge Zone during peak hours; $5.65 for pooled trips that did not use the Downtown Surcharge Zone, or did not occur during peak hours.

[3]Notably, Mayor Lori Lightfoot had originally campaigned with congestion pricing as part of her platform, but reportedly pivoted to tax only ridesharing companies as the advice of her cabinet.

Table 1 — Chicago Per-Trip Ridesharing Taxes

	Starts or Ends in Zone	Outside of Zone
Private Trip, Peak	\$3.00	\$1.25
Private Trip, Off Peak	\$1.25	\$1.25
Pooled Trip, Peak	\$1.25	\$0.65
Pooled trip, Off Peak	\$0.65	\$0.65

This tax schedule was implemented beginning on January 6$^{\text{th}}$, 2020, and replaced a flat tax of \$0.72 per trip (pooled and non-pooled). The downtown surcharge zone is as shown in Figure 2; peak hours are 6 am to 10 pm on weekdays. Private trips cover all non-pooled ridesharing options, regardless of the number of people in the vehicle.

4. Data

4.1. Ridesharing Trip and Price Data

I use the City of Chicago's trip-level ridesharing records to understand how trip prices and quantities adjusted in response to Chicago's ridesharing tax. Beginning in November of 2018, all ridesharing companies in Chicago were required to report their activity to the City of Chicago. Required disclosures include the trip termini, the price paid and tip for each trip, the trip type (shared or pooled), the trip start and end time, the distance traveled, and the trip time. A public version of these data are available through the Chicago Data Portal. In an effort to maintain the privacy of riders and protect proprietary ridesharing data, the City aggregates all trip termini to the Census Tract, rounds the timestamp to the nearest 15 minute, and rounds the price to the nearest \$2.50 before publishing the data.

A major empirical challenge is that the imposition of the GTT occurred three months before the beginning of the coronavirus pandemic. To avoid bias from the pandemic, I restrict the data to the months of November through February of 2018 through 2020 [4]

The resulting dataset consists of 34 million trip observations, each with an associated start and end location, start and end timestamp, fare, and tip. These data are summarized in Table 2 and Figures 15 and 14. The mean trip length is 4.8 miles; the mean trip price is \$13 (inclusive of fare, tax, tips, and other fees). The average trip speed of 16.8 miles per hour of significant congestion; Chicago sets a citywide surface-street speed limit of 30 miles per hour, with freeways ranging from 40 to 55 miles per hour.

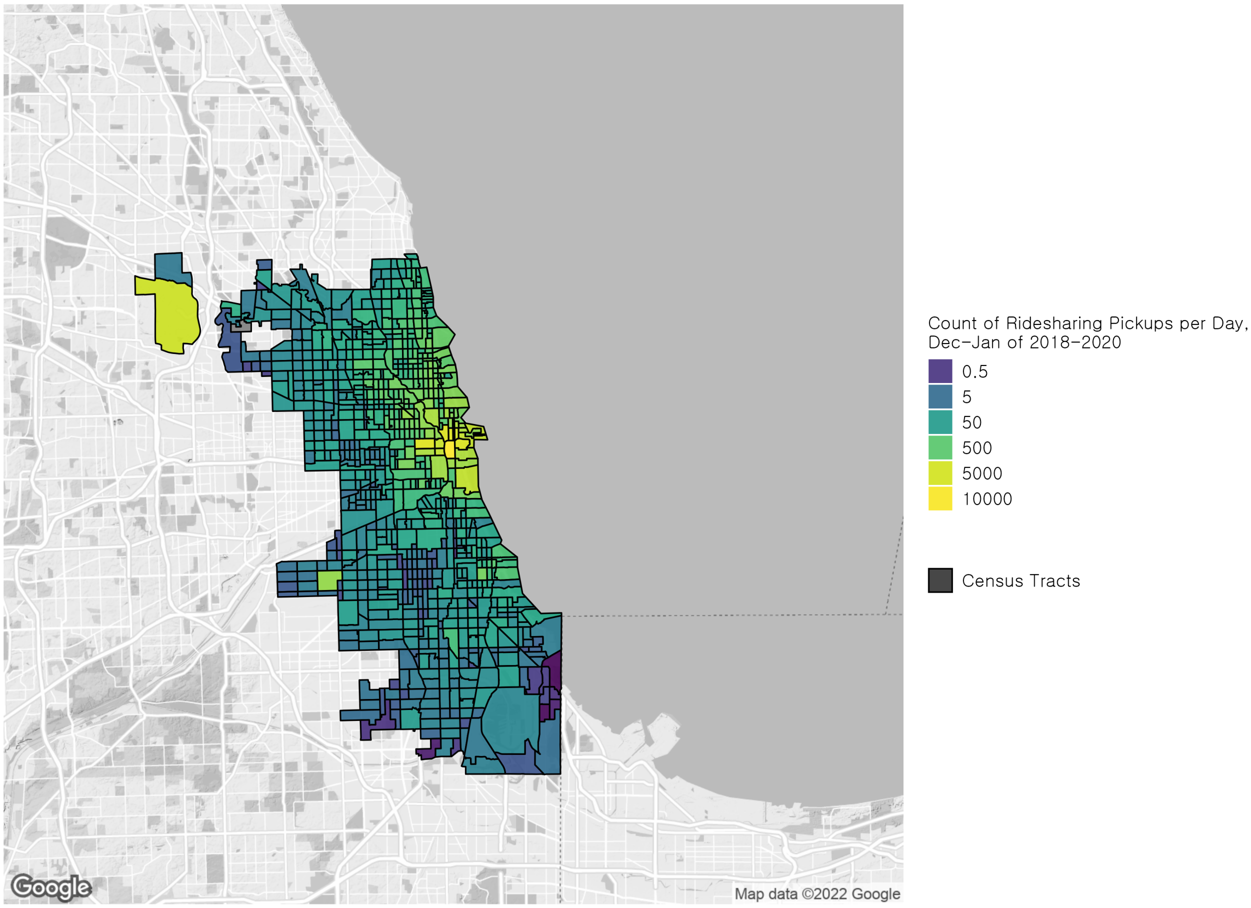
Table 2 — Chicago Ridesharing Data Summary Statistics

	Fare (\$)	Tip (\$)	Pooled	Miles	Speed (mph)	Dropoff in Zone	Pickup in Zone
Mean	9.61	0.48	0.15	4.77	16.84	0.35	0.35
SD	6.81	1.36	0.36	4.66	29.16	0.48	0.48

This Table summarizes the ridesharing data available through the City of Chicago Open Data Portal. To avoid bias induced by the COVID-19 pandemic, the data used in the paper (and summarized here) are restricted to November 2018 through February 15$^{\text{th}}$ 2020.

[4]For reference, Chicago announced its first shelter-in-place order on March 18$^{\text{th}}$, 2020, and Illinois issued a stay-at-home order on March 20, 2020.

Figure 9 — Ridesharing Activity in Chicago



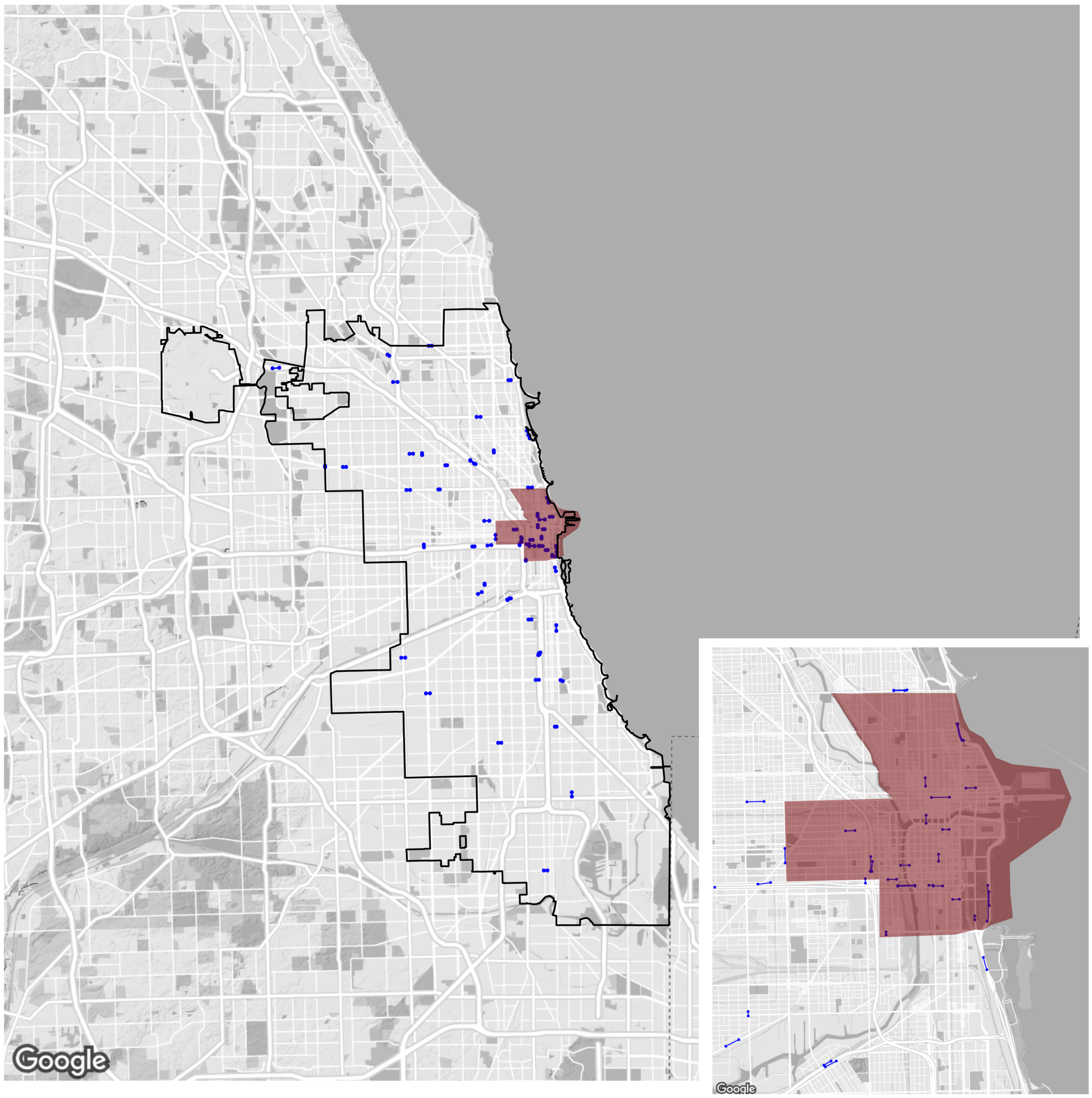
This Figure plots ridesharing pickups by Census Tract in Chicago from December 2018 through January 2020. These data are publicly available through the Chicago Data Portal.

4.2. Traffic Data

I use traffic data from two sources. The first source is TomTom's Historic Traffic Stats. I purchased data for 65 road segments in the greater Chicago area. These data are collected for January and February of both 2019 (prior to the tax increase) and 2020 (after the tax increase), and cover both the downtown toll zone as well as the surrounding city and neighborhoods. The start termini of these traffic segments were randomly selected from Chicago's traffic count locations, weighted by the number of trips at each station.

The second data source is ridesharing data themselves (described above). Each observation in the ridesharing data includes the trip distance (in miles) and the trip duration (in seconds). This provides a third source of speed data, and also facilitates granular matching comparisons.

Figure 4 — TomTom Traffic Segments



This Figure plots 65 TomTom traffic data segments in the Chicago area used to estimate the impact of the Downtown Surcharge on traffic speeds. The black line is the boundary of the city of Chicago; the red shaded region shown the area covered by the Downtown Surcharge.

4.3. Air Pollution Data

I use daily air pollution data from EPA Air Monitors in the city of Chicago and surrounding counties from 2018 to 2020 to investigate whether the GTT impacted air pollution. I focus on two species of pollution: NO_x and $PM_{2.5}$. I also use data from the EPAs Continuous Emissions Monitoring System (CEMS) for Chicago and the surrounding counties to control for activity that may confound estimates of the impact of Chicago's ground transportation tax on air pollution.

4.4. Demographic Data

I use data from the 2017 National Household Travel Survey (NHTS) to understand how ridesharing use differs across income. I compare the distributional burden of a tax on ridesharing to several other taxes using data from the 2017 Consumer Expenditure Survey (CEX).

5. Empirical Strategy

This section describes the regressions used to estimate the impact of Ridesharing Taxes (Chicago's Downtown Surcharge and/or Washington's Ridesharing Tax) on outcomes of interest.

Many of these specifications use differences in differences (DiD) or triple-differences (DDD) estimators. These approaches have recently received significant scrutiny and can yield biased results in certain settings (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). In this paper, I design all difference in differences and triple differences estimators to avoid the conditions that lead to biased estimands. Namely, in all regressions in this paper (a) the treatment variable only increases, (b) the treatment is binary, and (c) there is no variation in treatment timing —– all treatment indicators turn on at the same time. This approach avoids the bias induced by staggered DiD designs in the face of treatment effect heterogeneity (see page 4 of De Chaisemartin and D'Haultfoeuille, 2022). I further detail how the approaches in this section relate to recent DiD findings in the Appendix.

5.1. Trip Quantity and Price

To estimate the response of the ridesharing market to Chicago's Downtown Surcharge Zone, I use a triple differences estimator. I compare the outcome variables (15-minute average of trip prices, or 15-minute count of trips) of trips across three dimensions: (i) peak versus off-peak hours, (ii) before versus after the tax change, and (iii) with and without a terminus in the Downtown Surcharge Zone:

$$\begin{aligned} y_{r,t,d} =& \beta zone_r * peak_t * post_d + \\ & \gamma_1 zone_r * peak_t + \gamma_2 zone_r * post_d + \gamma_3 peak_t * post_d + \gamma_4 zone_r + \gamma_5 peak_t + \gamma_6 post_d + \Gamma X_{t,d} + \epsilon_{r,h,t} \end{aligned} \tag{1}$$

Where r indicates whether or not the trip has a terminus in the zone, t indicates time the trip was taken (rounded by the data provider to 15-minute increments), and d represents the date. The outcomes of interest, $y_{r,t,d}$, include levels and logs of trip prices and trip counts. $X_{r,t,d}$ consists of day-of-week fixed effects and two weather controls: a dummy variable for daily precipitation, and an indicator for days with high temperatures below 32 degrees.

5.2. Supply and Demand Elasticities

Following arguments made by Zoutman, Gavrilova, and Hopland (2018), I estimate the supply and demand elasticities using the ratio of the first-stage regression and the reduced-form regression

$$\epsilon^S = \frac{\pi_{zy}}{\pi_{zp}}, \qquad \epsilon^D = \frac{\pi_{zy}}{1+\pi_{zp}} \tag{2}$$

Where π_{zy} and π_{zp} reflect the respective coefficients from regressions of $log(quantity)$ and $log(price)$ on the instrument, z. In this setting, the instrument is a function of the tax rate, $log(1+\tau)$. The subscripts reflect that the data for these regressions are aggregated to the time of day, t, the date, d, and whether or not a trip uses the zone, r. Controls (X) include fixed effects for *zone*, *peak*, and *post*, as well as three two-way interactions between these variables. These fixed effects control for unobserved spatial and temporal determinants of demand that may be correlated with the tax levels.

$$log(\text{price of trips}_{t,d,r}) = \alpha + \pi_{zp} z_{t,d,r} + \gamma X_{t,d,r} + \epsilon_{t,d,r} \tag{3}$$
$$log(\text{number or trips}_{t,d,r}) = \alpha + \pi_{zy} z_{t,d,r} + \gamma X_{t,d,r} + \epsilon_{t,d,r}$$

This approach relies on an additional instrumental variables assumption (the Ramsey Exclusion Restriction). That is, in addition to the instrument being uncorrelated with the outcome (quantity), it also requires that the tax only impacts demand through after-tax prices, and supply through pre-tax prices.

5.3. Traffic Speeds

I estimate changes in traffic speeds using difference in differences and triple differences estimators.

Difference in Differences Estimator using TomTom Data:

$$\begin{aligned}(\frac{minutes}{mile})_{r,t,d} =& \beta zone_r * peak_t * post_d + \\ & \gamma_1 zone_r * peak_t + \gamma_2 zone_r * post_d + \gamma_3 peak_t * post_d + \gamma_4 zone_r + \gamma_5 peak_t + \gamma_6 post_d + \epsilon_{r,h,t}\end{aligned}$$

Difference in Differences Estimator using Ridesharing Data:
Chicago's ridesharing data provide a second data source to test whether traffic speeds changed in response to Chicago's downtown surcharge zone. Confining the analysis to peak hours, I compare traffic speeds pre vs. post policy inside versus outside of the zone, controlling for route (tract-tract fixed effects), and time of day (hour fixed effects). I include these fixed effects to control for compositional changes. Traffic speeds of TNC trips may change after the tax because traffic conditions themselves are different, or because riders take different trips, or travel at different times. I also restrict this analysis to only include the top 10% most frequently traveled tract-tract routes during the pre-tax period. These data account for roughly 50% of trips.

Each of these two approaches to estimating changes in traffic speeds comes with advantages and disadvantages. While the TomTom segments are fixed; the tract-tract trips have the advantage of giving a more complete view of how travel times change by reporting travel time differences that are inclusive of the endogenous re-routing that might occur when certain areas see extreme congestion.

$$(\frac{minutes}{mile})_{r,d,t} = \beta zone_r * post_d + \gamma_1 * post_d + \Gamma_2 \phi_r + \epsilon_{r,d,t}$$

5.4. Air Pollution

I estimate the impact of TNCs on air pollution by comparing $PM_{2.5}$ and NO_x pollution levels in the city of Chicago to pollution levels measured at upwind exurban and suburban air monitors before versus after the imposition of Chicago's GTT. I also control for NO_x and SO2 emissions (both of which are precursors to $PM_{2.5}$) inside Chicago versus in the exurbs/suburbs using data from the EPA's continuous emissions monitoring system.

5.5. Threats to Identification

The difference in differences approach described here is subject to a number of well-known threats to identification. These include concerns about heterogeneous treatment effects, SUTVA violations, and issues related to the use of log-transformed outcome variables. I discuss each of these concerns in Appendix A.

6. Results

6.1. Stylized result 1: The Demand for ridesharing is inelastic relative to supply

Table 6.1 shows results from Equation 1, a triple differences specification used to estimate changes in the count and price of trips in response to the increase in ridesharing taxes.

Plugging in the results from Columns (1) and (2) of Table 6.1 into Equation 2 yields an elasticity of demand of -0.15. This suggests ridesharing demand is inelastic, with an elasticity similar to other studies of private vehicle demand. Gibson and Carnovale (2015) for example, collects 13 estimates of the price elasticity of private vehicle travel with respect to tolling, 8 of which are larger (more elastic) than -0.15. The elasticity of supply implied by Table 6.1 is -0.96. This estimated supply elasticity is similar to but smaller smaller than those reported by Angrist, Caldwell, and Hall (2021) (-1.2) and Chen et al. (2019) (-1.92).

These result suggests that ridesharing demand is inelastic not just relative to supply, but in gross terms as well. The distinction between relative elasticity and absolute elasticity is important when considering (a) reductions in externalities associated with ridesharing, and (b) the efficiency of collecting revenue through a ridesharing tax.

Table 6.1 — The Elasticity of Ridesharing Demand

	Log(Count of Trips)	Log(Trip Price)
Log (Tax + 1)	-0.181***	0.187***
	(0.056)	(0.021)
Zone x Peak	0.687***	0.023***
	(0.023)	(0.009)
Zone x Post	0.039*	0.009
	(0.023)	(0.009)
Peak x Post	0.084***	0.012
	(0.021)	(0.008)
Post	0.304***	-0.003
	(0.016)	(0.006)
Peak	1.080***	0.057***
	(0.015)	(0.006)
Zone	0.026	-0.060***
	(0.016)	(0.006)
Int.	2.495***	2.373***
	(0.036)	(0.013)
Num. obs.	79343	79343

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

This table displays the results of two instrumental variables regressions that estimate the change in the number of ridesharing trips in response to the imposition of Chicago's Ground Transportation Tax. The dependent variable is rides per 15-minute period. *Zone* is a dummy for whether or not a given trip uses the downtown surcharge zone. *Peak* is a dummy for whether the trip was taken at peak hours. *Post* is a dummy for whether the trip was taken after the policy was imposed. The data used to estimate this regression are publicly accessible through Chicago's Open Data Portal.

6.2. Stylized result 2: Passengers bear the majority of the cost of ridesharing taxes

The supply and demand elasticities (-0.96 and -0.15, respectively) estimated in the previous section imply that consumers bear roughly 86% of the ridesharing tax. The remaining 14% is split between drivers and the ridesharing companies. Both Uber and Lyft take 25% commission from fares (and none from tips). This implies that drivers bear between 10.5 and 14% of the ridesharing tax in Chicago, depending on the split between fare income (which is subject to Uber's 25% commission) and tip income (which is not subject to commission).

Because the incidence of taxes on ridesharing depends on the relative elasticities of supply and demand, caution should be taken in applying these findings to cities where the supply of Uber or Lyft drivers is capped. New York, for example, limits the number of ridehailing permits. In this setting, a tax on TNCs would likely fall heavily on the inelastic supply side (Marion and Muehlegger, 2011). Relatedly, these elasticities are short-term to medium-term; it is not immediately clear which side (supply or demand) we should expect to become relatively more elastic over the long run.

I find little response in tipping. Appendix Figure 12 shows that as compared to non-taxed trips, trips subject to the ridesharing tax were accompanied by slightly larger tips. This result appears to be mechanical: Figure 13 shows little evidence that the tip rate varied for trips subject to the surcharge.

6.3. Stylized result 3: On a per-capita basis, drivers face a higher burden from ridesharing taxes

What do these impacts translate to in terms of changes in revenue and costs at the driver or rider level? The revenue lost by drivers is equal to the trip price times the change in total trips completed, plus the change (after-tax) prices multiplied by the number of inframarginal trips. That is, $R' = p'q + q'p$.

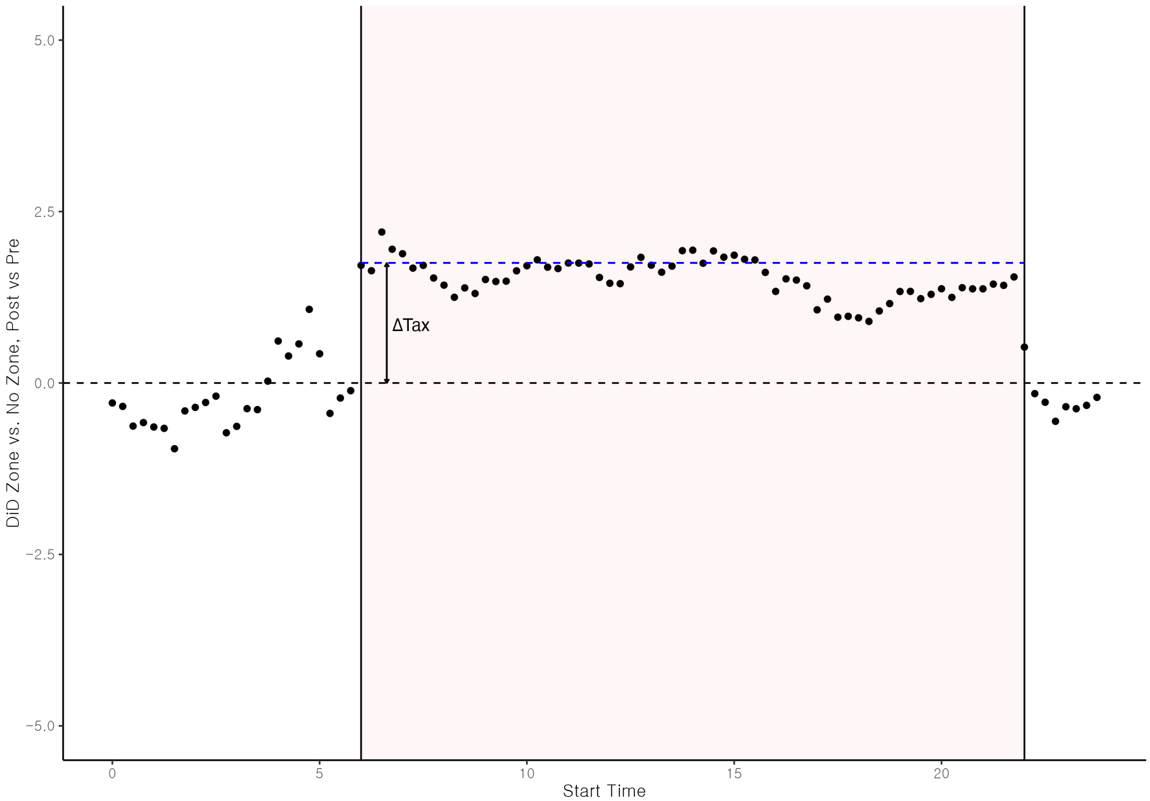
The average driver provides 63 rides per month. 42% of all trips in the post period were subject to the \$3.00 downtown surcharge; with the remaining 58% subject to the flat rate of \$1.25. Assuming a pass-through rate of 86%, and that Uber takes 25% of fares, this implies that drivers on average see a reduction in income of roughly $(63) * (0.75 * 0.14) * (0.42 * \$3.00 + 0.58 * \$1.25) = \$13.13$ dollars per month via lower prices. Regarding lost revenue from a reduction in the overall number of trips, the average tax of \$1.99 and average trip price of \$9.61 implies that the cumulative taxes increase prices by 22% on average. The price elasticity of demand of -0.15 implies that the number of trips is 3.3% lower than it would be in the absence of these taxes. This reduction in trips implies an additional $(0.033) * (63) * (\$9.610) = \$19.98$ in lost revenue per month.

On average, drivers therefore lost roughly \$33.11 per month due to Chicago's ridesharing taxes. This is roughly 5.4% of the average monthly revenue from riders.[5]

Data from the NHTS suggests that the average resident of Chicago takes 0.5 trips per month. Among people who report using ridesharing services, this figure is 4.3 rides per month. Assuming a pass-through rate of 85% and an average tax rate of \$1.99, these taxes cost the average ridesharing user pays \$7.27 dollars in ridesharing taxes per month. Using all of Chicago (ridesharing users and non-ridesharing users) reduces the average monthly tax incidence to \$0.85.

[5]Note: This revenue calculation does not address the marginal increase in pooled rides resulting from the change in taxes.

Figure 5 — Change in Ridesharing Trip Prices



This figure provides a visual depiction of the triple differences estimator used to estimate the pass-through of the ridesharing tax. Each point in the Figure plots a difference in differences for a given 15-minute interval of the day. The first difference compares trips that use the downtown surcharge zone to those that don't use the downtown surcharge zone. The second difference compares is pre policy vs. post policy. The third difference compares peak and off-peak hours —– the downtown surcharge zone only applies between the hours of 6 am and 10 pm. This difference is the vertical distance between points inside and outside of the red shaded region. The blue dotted line at $1.75 is the change in the tax rate.

Table 6.3 — Price Per Trip

	Trip Price	Trip Price
Zone x Peak x Post	1.77***	
	(0.19)	
Zone x Peak	-0.49***	
	(0.13)	
Zone x Post	-0.27*	
	(0.15)	
Peak x Post	0.22*	1.29***
	(0.13)	(0.01)
Post	0.82***	0.49***
	(0.11)	(0.01)
Peak	-0.08	0.83***
	(0.09)	(0.01)
Zone	0.94***	
	(0.11)	
Num. obs.	12493	4734121

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

This table displays the results of two triple differences regressions that estimate the change in the price of ridesharing trips in response to the imposition of Chicago's Ground Transportation Tax. The dependent variable is price per trip. *Zone* is a dummy for whether or not a given trip uses the downtown surcharge zone. *Peak* is a dummy for whether the trip was taken at peak hours. *Post* is a dummy for whether the trip was taken after the policy was imposed. The data used to estimate this regression are publicly accessible through Chicago's Open Data Portal.

6.4. Stylized result 4: There is little evidence that taxing ridesharing meaningfully reduces air pollution or congestion

Air Pollution

Table 6.4 displays the results several a difference in differences regressions used to estimate the impact of Chicago's GTT on air pollution in the city. I estimate the impact on two types of pollution: particulate matter ($PM_{2.5}$) and nitrogen oxides (NO_x). For each species, I estimate three specifications, (1) a difference in differences in logged pollution levels, (2) a difference in differences specification in logged pollution levels that controls for point-source emissions, and (3) a difference in differences specification in levels that controls for point-source emissions. In each case, the "treated" group includes sensors inside the city of Chicago, and the "not treated" group includes sensors that are outside of the city of Chicago, but within 100 miles of the city, and lie west (typically upwind) of the city.

Overall, I find little evidence that taxing ridesharing impacts air pollution. 5 out of 6 estimates have positive point estimates. Decreases in air quality could be driven by substitution to private (dirtier) vehicles, or changes in the composition of the ridesharing fleet in response to these taxes. Importantly, however, these estimates are not statistically significant. While I can generally reject with 95% confidence improvements in particulate matter larger than 5%, I cannot reject economically meaningful increases in air pollution resulting from these policies, nor can I reject meaningful improvements in NO_x emissions.

Traffic Congestion

Tables X and Y show the results of using equations XX and YY to estimate changes in traffic speeds in downtown Chicago following the imposition of the GTT. Table X uses traffic data purchased from TomTom; Table Y uses travel time data from the TNCs themselves. Each table shows the same two specifications: a difference in differences comparing traffic speeds inside versus outside of the zone before versus after the imposition of the GTT, and a triple differences estimator where the additional difference compares peak to off-peak hours.

Both specifications . Unlike air pollution results, these estimates are precise enough to reject large changes resulting from the GTT. Both estimates in Table Y can reject with 95% confidence changes increases in traffic speeds of more than 3%; both columns from Table Y can reject increases in traffic speeds of more than 0.1% with 95% confidence.

Back of the envelope calculations using the elasticities reported above suggest that we should not expect large changes in traffic absent significant substitution or GE effects. If ridesharing trips decreased by roughly 3% following the introduction of the tax, and ridesharing trips represent roughly 10% of urban VMT, then the direct change in traffic induced by these policies is a 0.3% reduction in overall VMT.

TABLE 6.4 — AIR POLLUTION

	PM2.5			NO2		
	Log PM	Log PM	PM Levels	Log NO2	Log NO2	NO2 Levels
Post x Treated	0.08	0.06	0.60	0.04	0.04	-0.68
	(0.07)	(0.07)	(0.89)	(0.09)	(0.09)	(1.05)
Post	-0.05	-0.02	0.06	-0.12	-0.08	-0.10
	(0.05)	(0.05)	(0.62)	(0.06)	(0.06)	(0.75)
SO2 CEMS Control		0.04	0.35		0.07^{*}	0.62
		(0.03)	(0.33)		(0.03)	(0.40)
NOx CEMS Control		0.07^{**}	0.51^{*}		0.12^{***}	1.51^{***}
		(0.02)	(0.26)		(0.03)	(0.31)
Post FE	Yes	Yes	Yes	Yes	Yes	Yes
Sensor FE X Month of Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	4119	4099	4099	3409	3409	3409

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

This table shows the results of differences in differences regressions that estimate the change in air pollution (particulate matter and nitrogen oxides) resulting from taxing ridesharing in Chicago and Washington DC. Each regression compares daily mean pollution levels from within Chicago to levels in the counties upwind of Chicago. The air pollution data used in these regressions are courtesy of the EPA's air pollution monitor network. *Post* is an indicator observations in either a control or treated city that take place in after the ridesharing tax began in Chicago. The Treated fixed effect is not included because it is subsumed in the sensor-level seasonal controls.

Table 6.4 — TomTom Traffic Speed

	Log (Minutes per Mile)(Diff-in-Diff)	Log (Minutes per Mile)(Triple Diff)
Post * Treatment Year * Inside		0.008
		(0.023)
Peak * Inside		0.069
		(0.043)
Post * Inside	0.035	0.024
	(0.035)	(0.037)
Post * Inside	0.035	0.024
	(0.035)	(0.037)
Post	-0.047*	-0.034
	(0.019)	(0.021)
Hour of Day FEs	Yes	Yes
Route FEs	Yes	Yes
Weather Controls	No	No
Num. obs.	21959	35068

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

This table shows the results of differences in differences and triple differences regressions that estimate the change in traffic speed resulting from Chicago's imposition of its Ground Transportation Tax. The data for this regression were purchased from TomTom, and consist of weekly speed data for 65 traffic segments. The time period coverage is November through February of the both the 2018-2019 and the 2019 to 2020 winters. The first regression includes only peak hours (6 am to 10 pm); the second regression includes all hours. The first regression compares differences before versus after the tax change for regions inside versus regions outside of the surcharge zone. The second regression adds a third dimension of difference: peak hours (when the tax was in place) vs. off-peak hours (when the policy was not in place). The fixed effect for *Inside* is dropped for the first regression and fixed effects for *Inside* and *Peak* are dropped from the second regression because both regressions include more granular fixed effects for route and time of day.

Table 6.4 — Estimating Changes in Traffic Speeds using Ridesharing Data

	Log(Minutes per Mile)	Log(Minutes per Mile)
Zone x Peak x Post		0.003
		(0.002)
Zone x Peak		0.032***
		(0.002)
Zone x Post	0.033***	0.023***
	(0.002)	(0.003)
Peak x Post		-0.009***
		(0.002)
Post	-0.078***	-0.067***
	(0.002)	(0.002)
Hour of Day FEs	yes	yes
Route FEs	yes	yes
Weather Controls	yes	yes
Num. obs.	8685743	3109123

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

This table shows the results of two regressions that use ridesharing trip data to estimate changes in traffic speeds in Chicago in response to the imposition of the Downtown Surcharge Zone. The first column is a difference in differences comparing ridesharing trip speeds before versus after the imposition of the policy on routes with a terminus in the Downtown Surcharge Zone versus routes without a terminus in the Downtown Surcharge Zone. A route is defined as a pair of census tracts. The second column is a triple differences strategy that uses aggregated speed data the route-hour-date level. The third dimension of difference is comparing peak (6 am to 10 pm) versus off-peak travel times. In both regressions, *zone* and *peak* fixed effects are omitted because they are subsumed by *route* and *hour* fixed effects. Weather controls include and indicator for days with precipitation and an indicator for days below 32 degrees Fahrenheit.

[Washington DC Traffic Congestion Table Here]

[Washington DC Traffic Air Pollution Table Here]

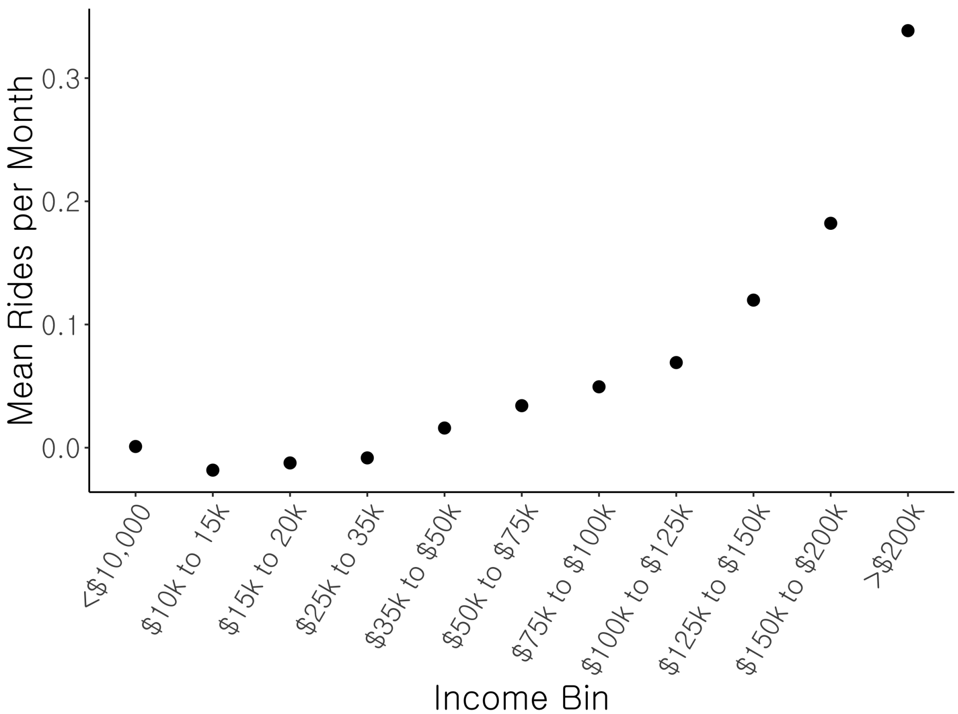
6.5. Stylized result 5: Ridesharing taxes are progressive

Using data from the National Household Travel Survey, I show that ridesharing use increases with income. This pattern holds both for urban areas at the aggregate level (see Figure 6) as well as within individual urban areas see Figure 7).

An important distinction often absent from policy debates is the distinction between *proportional* and *absolute* progressivity. For example, while high-income households spend more on gasoline than do low-income households, this gasoline consumption increases less than proportionally with income. Gasoline taxes are therefore absolutely progressive but proportionally regressive.

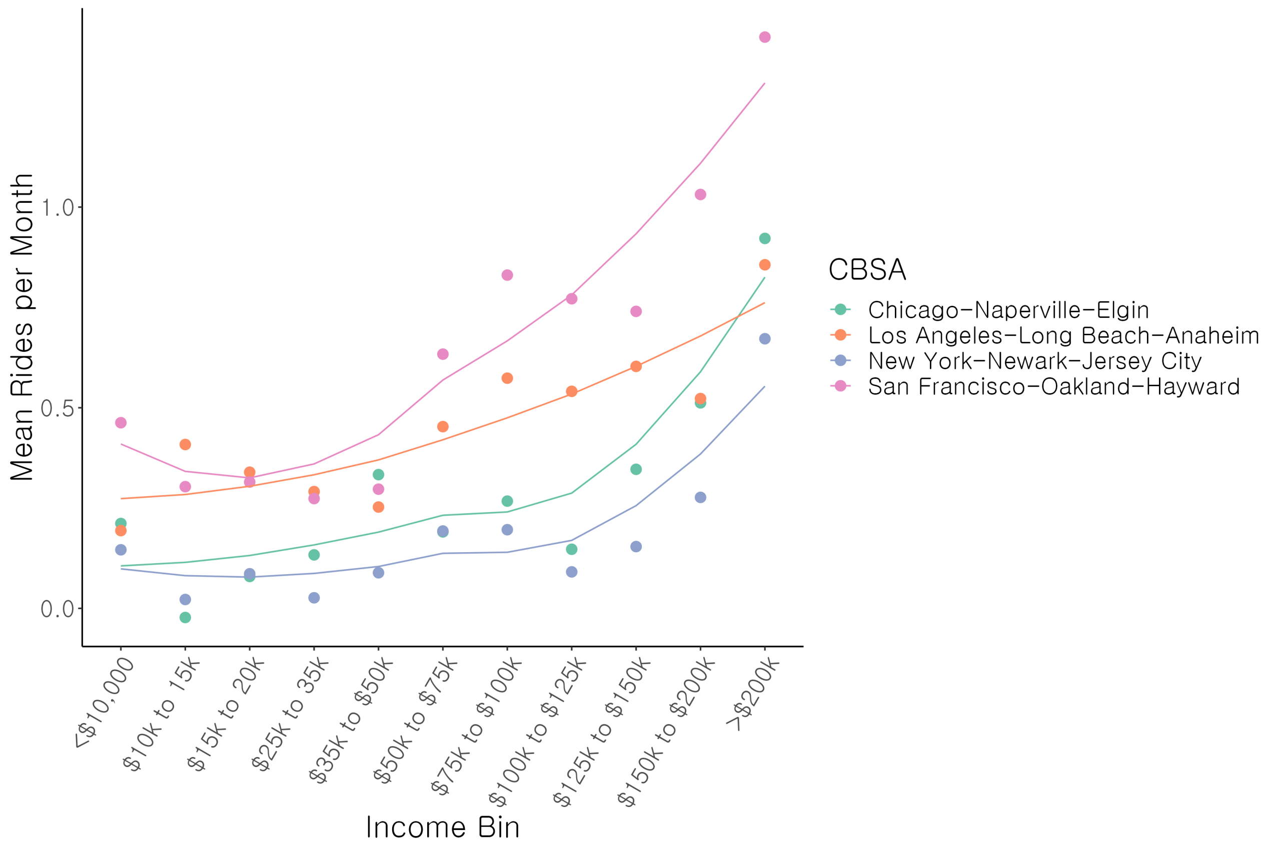
Figure 8 shows that on average, high-income households would pay a larger fraction of their income in per-trip ridesharing taxes making these taxes proportionally progressive. Figure 8 and Table 3 compare the progressivity of ridesharing taxes to other taxes often used to finance state or local public goods. Property and Gasoline Taxes are proportionally regressive; ridesharing taxes are roughly as progressive as the federal income tax schedule.

Figure 6 — TNC Rides by Income



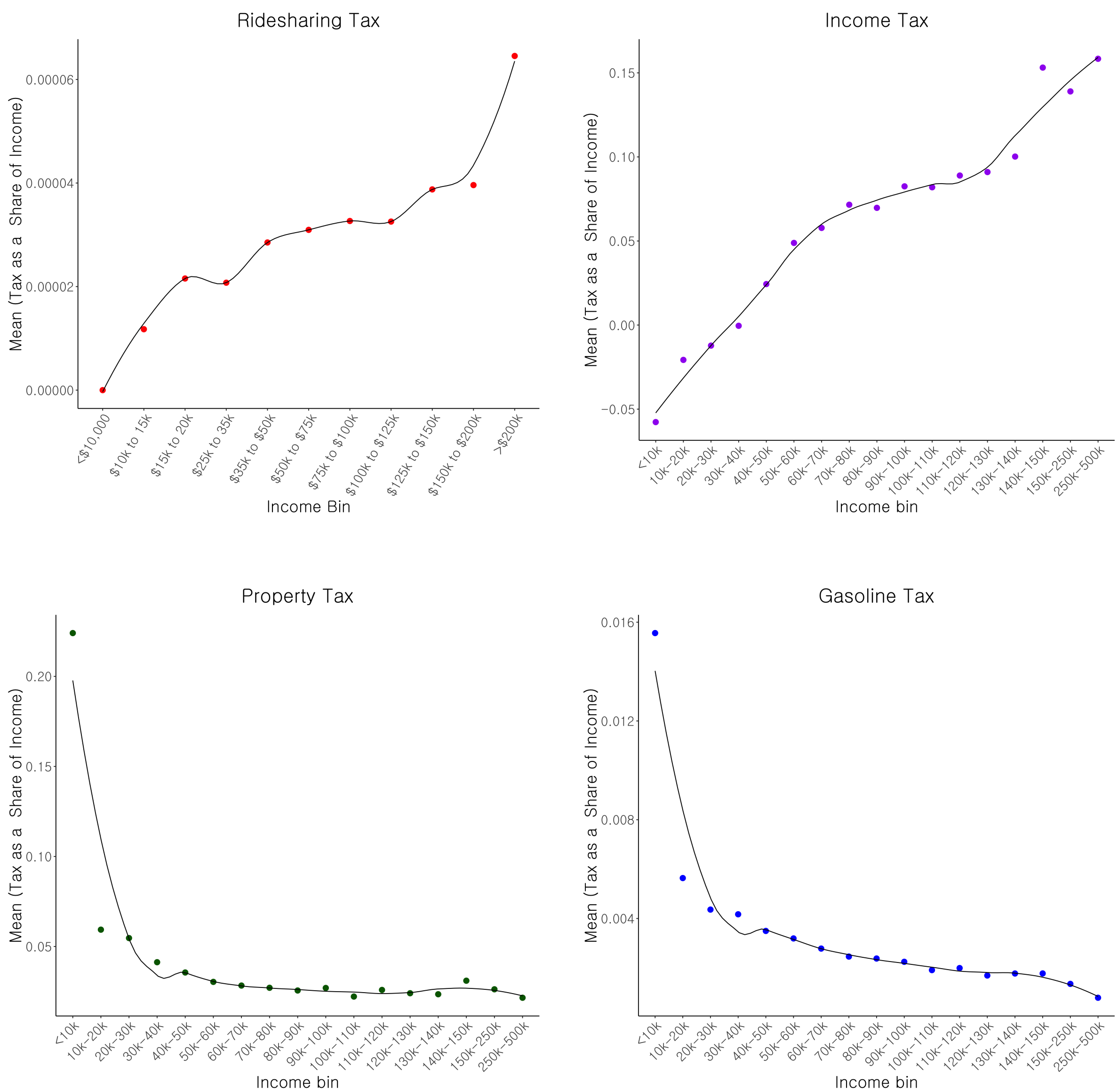
This figure plots average TNC rides per month by income group, as per the 2017 NHTS. I restrict this figure to consider only NHTS responses by individuals who live in an “Urban Area” or an “Urban Cluster.” The NHTS does not report data on spending on ridesharing.

Figure 7 — TNC Rides by Income for Select US Metros



This figure uses plots average TNC rides per month by income group for select US Metros. The data for this figure come from the 2017 NHTS. The NHTS does not report data on spending on ridesharing. As such, this figure best describes the incidence of a specific tax on ridesharing rather than an ad valorem tax.As such, this figure best describes the incidence of a specific tax on ridesharing rather than an ad valorem tax.

Figure 8 — Distributional Burdens of Various Taxes



This figure plots the tax burden as a share of income for a ridesharing tax (upper left) against three other taxes: income taxes (upper right), property taxes (lower left), and gasoline taxes (lower right). Data for the distributional burden of ridesharing taxes come from the 2017 National Household Travel Survey, where respondents report their ridesharing usage (number of rides) in the month leading up to their interview date. The other three panels reflect data from the consumer expenditure survey. Each point reflects mean of the proportional burden (tax burden divided by income) for individuals in a given income bracket. Prior to taking the mean of the data, proportional burdens were winsorized at the 1% level. The black line is a local polynomial fit.

Table 3 — Progressivity of Tax Burdens

		Tax		
	Ridesharing	Income	Property	Gas
Normalized Slope of Tax Burden	0.076	0.091	-0.051	-0.061

This table displays the normalized slope of each of the panels in Figure 8. Each cell reflects the coefficient of a regression of the mean normalized proportional tax burden on the midpoint of income for a given income bin. Positive numbers indicate proportionally progressive taxes; negative numbers indicate proportionally regressive taxes. The proportional tax burdens are normalized (divided by the mean proportional burden across all income bins) to facilitate comparison of the degree of progressivity across taxes. Incomes were measured in tens of thousands of dollars.

6.6. Ridesharing, Public Transit, and Optimal Taxes

As a final note, it is worth discussing the connection between ridesharing, public transit, and optimal ridesharing taxes. Several papers find that ridesharing is a complement to public transit, most notably Hall, Palsson, and Price (2018). Following this notion, cities have implemented or are piloting programs to subsidize ridesharing trips to public transit stops.

Does this complementary matter for setting optimal prices on Uber and Lyft? Seminar work on second-best taxation and "direct" versus "indirect" taxation provide insight into this question (Green and Sheshinski, 1976; Sandmo, 1978).

Imagine a representative consumer who consumes four goods: driving (x), public transit (y), ridesharing (z), and a numeraire (m). The consumer has an exogenous income, μ. Ridesharing and driving generate untaxed externalities ϕ_z and ϕ_x, respectively. Imagine also that public transit may or may not be priced such that marginal social cost equals marginal social benefit. Let the wedge between marginal social cost and marginal social benefit be γ.[6]

The consumer's problem is:

$$max\{u(x,y,z)+m\} \qquad s.t. \qquad \mu \geq m + p_x x + p_y y + p_z z \tag{4}$$

The social planner's problem is:

$$max\{u(x,y,z)+m-\phi_x x-\phi_z z-\gamma y\} \qquad s.t. \qquad \mu \geq m + p_x x + p_y y + (p_z) z \tag{5}$$

By (a) solving the consumer's problem, and (b) plugging in the consumer's first-order conditions into the social planner's problem, the optimal tax τ on ridesharing can be shown to be:

$$\tau* = \underbrace{\phi_z}_{\text{Direct}} + \underbrace{\phi_x \frac{\frac{\partial x}{\partial \tau}}{\frac{\partial z}{\partial \tau}} + \gamma \frac{\frac{\partial y}{\partial \tau}}{\frac{\partial z}{\partial \tau}}}_{\text{Indirect}} \tag{6}$$

[6]Note that because driving and ridesharing externalities are included here, γ should not be taken to include the foregone emissions or congestion externalities from substitution between rail and auto transport.

This is an informative expression. The cross-price elasticity (derivative) between ridesharing and public transit only matters in determining optimal ridesharing taxes insofar as there is a wedge between the price and the social marginal benefit of public transportation ($\gamma \neq 0$). Said differently, if the Samuelson condition holds for public transit, then there is no pre-existing distortion, and it is irrelevant for setting optimal ridesharing taxes whether ridesharing and public transit are complements or substitutes.

7. Conclusion

This paper investigates three first-order concerns regarding taxing ridesharing companies: how effective are these taxes at addressing externalities, how efficiently do these taxes raise revenue, and who bears the burden of these taxes. Using data from Chicago, I find that the demand for ridesharing is inelastic both in gross terms, and relative to the supply of ridesharing trips. This result has a number of implications. First, ridesharing taxes are borne largely by consumers. Second, ridesharing taxes do not appear to generate significant improvements in air pollution or traffic congestion. And third, raising revenue via ridesharing taxes appears to be an efficient (Ramseyan) way for local governments to raise tax revenue. Finally, using data form the NHTS and CEX, I shows that ridesharing taxes are roughly as progressive as the income tax schedule (inclusive of EITC and other direct transfers).

Together, these results suggest that ridesharing taxes may be an appealing instrument for cities, but perhaps not for the reasons that they often claim. That is, ridesharing taxes should not be expected to deliver significant reductions in congestion or pollution.

Finally, it is worth noting the limitations of this paper. First, the demand and supply elasticities estimated in this paper are short- to medium-term; it is not obvious how the relative elasticity or ridesharing demand and supply should evolve in the long term. Second, Chicago does not impose a ceiling on the number of ridesharing vehicles. Some cities, like New York, do regulate the total amount of for-hire vehicles. If the supply constraints are binding, we should expect the pass-through in these markets to be quite different, and for drivers to bear a significantly larger fraction of the burden of ridesharing taxes imposed on top of these existing regulations.

References

Angrist, Joshua D, Sydnee Caldwell, and Jonathan V Hall. 2021. "Uber versus taxi: A driver's eye view." *American Economic Journal: Applied Economics* 13 (3):272–308.

Callaway, Brantly and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics* 225 (2):200–230.

Chen, M Keith, Peter E Rossi, Judith A Chevalier, and Emily Oehlsen. 2019. "The value of flexible work: Evidence from Uber drivers." *Journal of political economy* 127 (6):2735–2794.

Christensen, Peter and Adam Osman. 2021. "The Demand for Mobility: Evidence from an Experiment with Uber Riders." .

Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. 2016. "Using big data to estimate consumer surplus: The case of uber." Tech. rep., National Bureau of Economic Research.

De Chaisemartin, Clément and Xavier D'Haultfoeuille. 2022. "Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey." Tech. rep., National Bureau of Economic Research.

Erhardt, Gregory D, Sneha Roy, Drew Cooper, Bhargava Sana, Mei Chen, and Joe Castiglione. 2019. "Do transportation network companies decrease or increase congestion?" *Science advances* 5 (5):eaau2670.

Fullerton, Don and Gilbert E Metcalf. 2002. "Tax incidence." *Handbook of public economics* 4:1787–1872.

Gibson, Matthew and Maria Carnovale. 2015. "The effects of road pricing on driver behavior and air pollution." *Journal of Urban Economics* 89:62–73.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics* 225 (2):254–277.

Green, Jerry and Eytan Sheshinski. 1976. "Direct versus indirect remedies for externalities." *Journal of Political Economy* 84 (4, Part 1):797–808.

Hall, Jonathan D, Craig Palsson, and Joseph Price. 2018. "Is Uber a substitute or complement for public transit?" *Journal of urban economics* 108:36–50.

Kotlikoff, Laurence J and Lawrence H Summers. 1987. "Tax incidence." In *Handbook of public economics*, vol. 2. Elsevier, 1043–1092.

Krishnamurthy, Chandra Kiran, Nicole S Ngo et al. 2022. "Do ride-hailing services worsen freeway congestion and air quality? Evidence from Uber in California." *Center for Environmental and Resource Economics, CERE, Do ride-hailing services worsen freeway congestion and air quality* .

Lehe, Lewis, Sairpaneeth Devunuri, Javier Rondan, and Ayush Pandey. 2021. "Taxation of Ride-hailing." Tech. rep., Illinois Center for Transportation/Illinois Department of Transportation.

Marion, Justin and Erich Muehlegger. 2011. "Fuel tax incidence and supply conditions." *Journal of public economics* 95 (9-10):1202–1212.

Mayor's Press Office. 2019. "Mayor Lightfoot Announces New Regulations to Ease Traffic Congestion and Encourage Sustainable Transit Use Throughout Chicago." *Chicago Office of the Mayor* .

Ramsey, Frank P. 1927. "A Contribution to the Theory of Taxation." *The economic journal* 37 (145):47–61.

Sandmo, Agnar. 1978. "Direct versus indirect Pigovian taxation." *European Economic Review* 7 (4):337–349.

Sarmiento, Luis and Yeong Jae Kim. 2021. "The Air Quality Effects of Uber." Tech. rep.

Tarduno, Matthew. 2021. "The congestion costs of Uber and Lyft." *Journal of Urban Economics* 122:103318.

Uber. 2019. "A fairer way to fight congestion and raise $21 million more in revenue." *Uber Blog* .

Ward, Jacob W, Jeremy J Michalek, and Constantine Samaras. 2021. "Air pollution, greenhouse gas, and traffic externality benefits and costs of shifting private vehicle travel to ridesourcing services." *Environmental Science & Technology* 55 (19):13174–13185.

Zoutman, Floris T, Evelina Gavrilova, and Arnt O Hopland. 2018. "Estimating both supply and demand elasticities using variation in a single tax rate." *Econometrica* 86 (2):763–771.

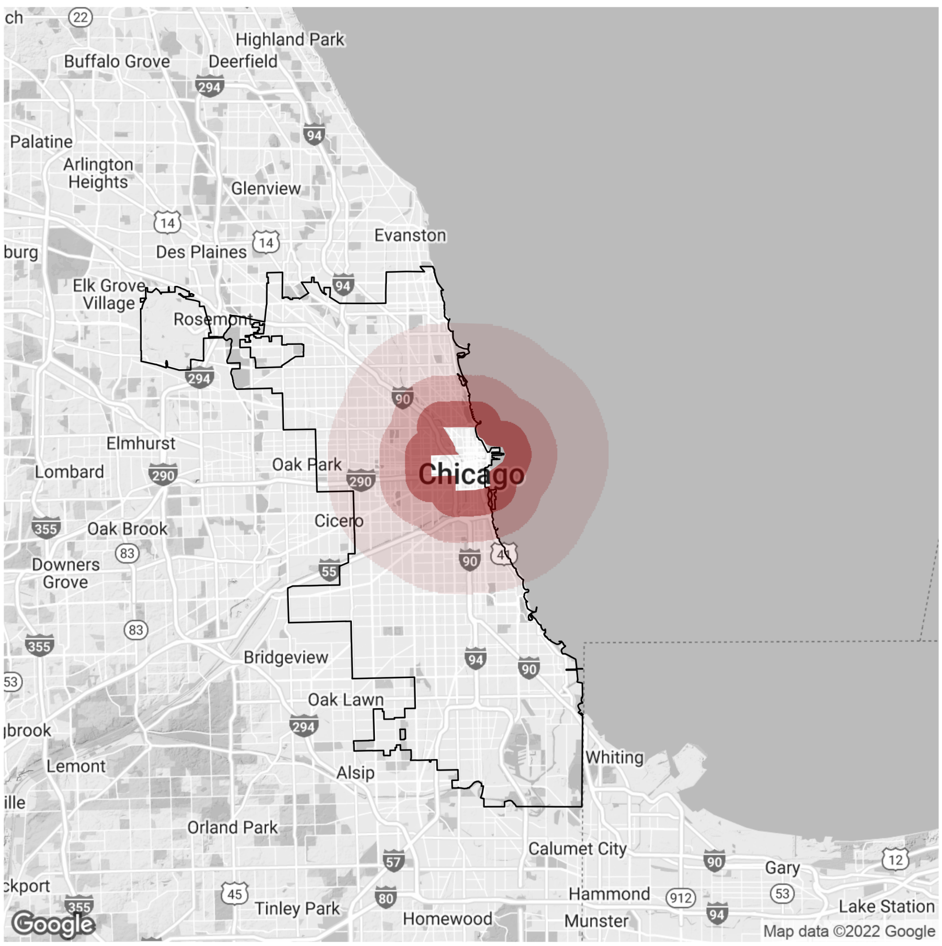
Appendix (in progress)

A. Threats to Identification

Spillovers present a serious threat to identification in spatial and temporal difference in differences estimators. To address this threat, I modify the equations used to estimate changes in prices and quantities of ridesharing trips to include spatial and temporal buffer zones (see below). I run a battery of regressions, including (a) spatial buffer zones of 2, 4, and 8km, as well as a version of the triple differences estimator that drops one hour on each side of the peak-hour pricing window.

A.1. SUTVA

Figure 9 — Buffer Zones to Address Geographic Spillovers



This Figure plots 2km, 4km, and 8km buffers around Chicago's Downtown Surcharge Zone.

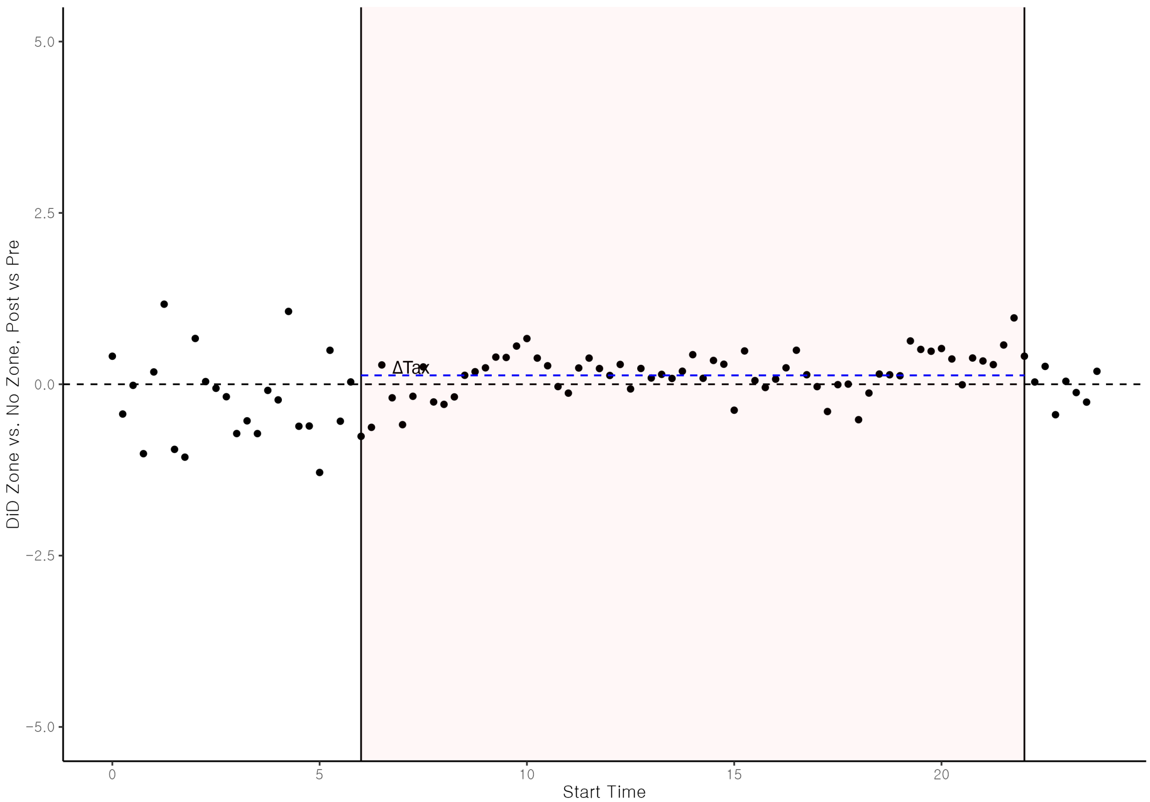
[SUTVA Table Here]

A.2. Parallel Trends

[Parallel Trends Test Here]

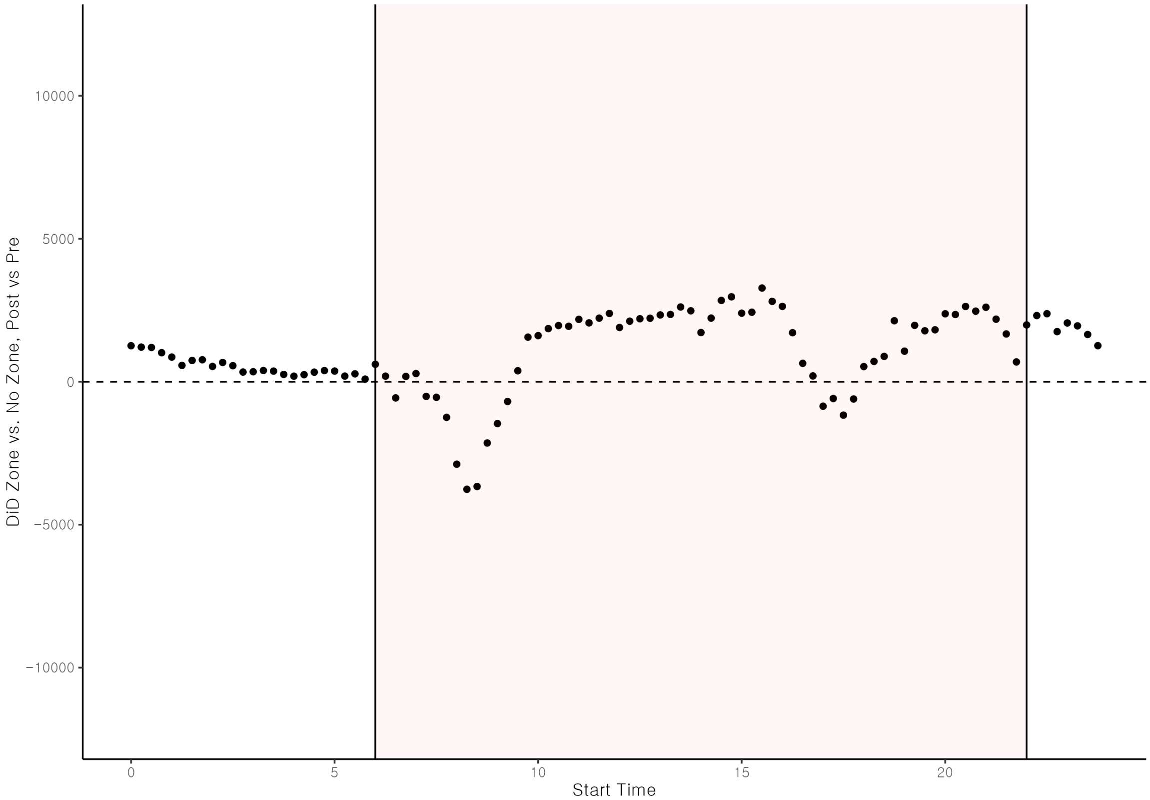
B. Additional Figures

Figure 10 — Change in Pooled Trip Prices



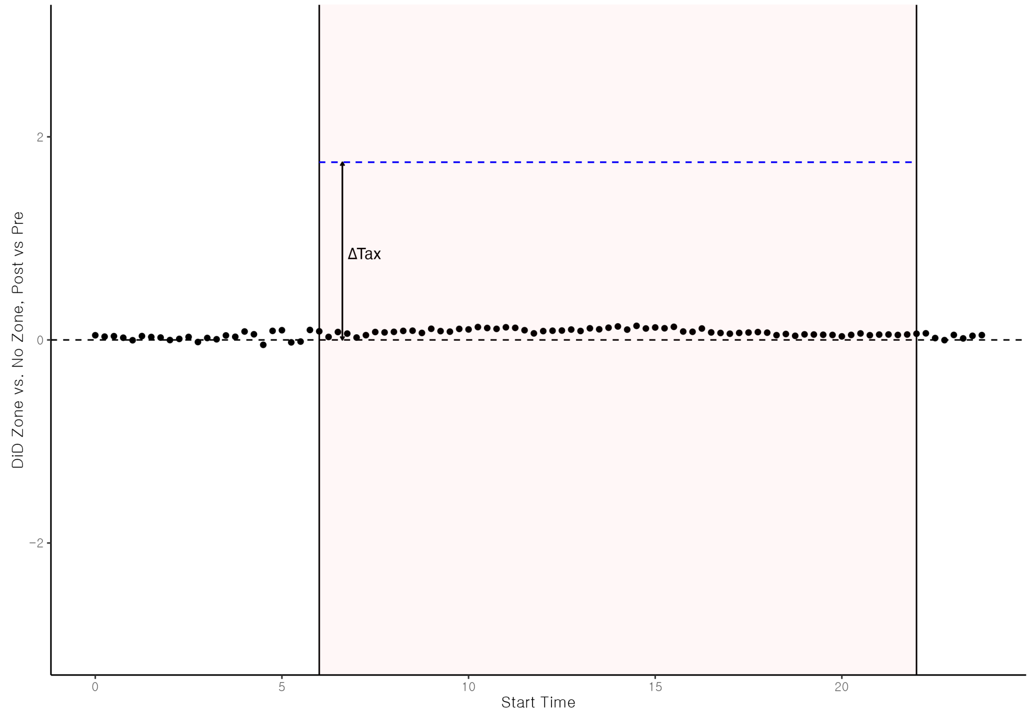
This figure provides a visual depiction of the triple differences estimator used to estimate the pass-through of the ridesharing tax. Each point in the Figure plots a difference in differences for a given 15-minute interval of the day. The first difference compares trips that use the downtown surcharge zone to those that don't use the downtown surcharge zone. The second difference compares is pre policy vs. post policy. The third difference compares peak and off-peak hours —– the downtown surcharge zone only applies between the hours of 6 am and 10 pm. This difference is the vertical distance between points inside and outside of the red shaded region. The blue dotted line at $0.13 is the difference in the change in the pooled trip tax rate between peak and off-peak hours in the surcharge zone.

Figure 11 — Change in Pooled Trip Counts



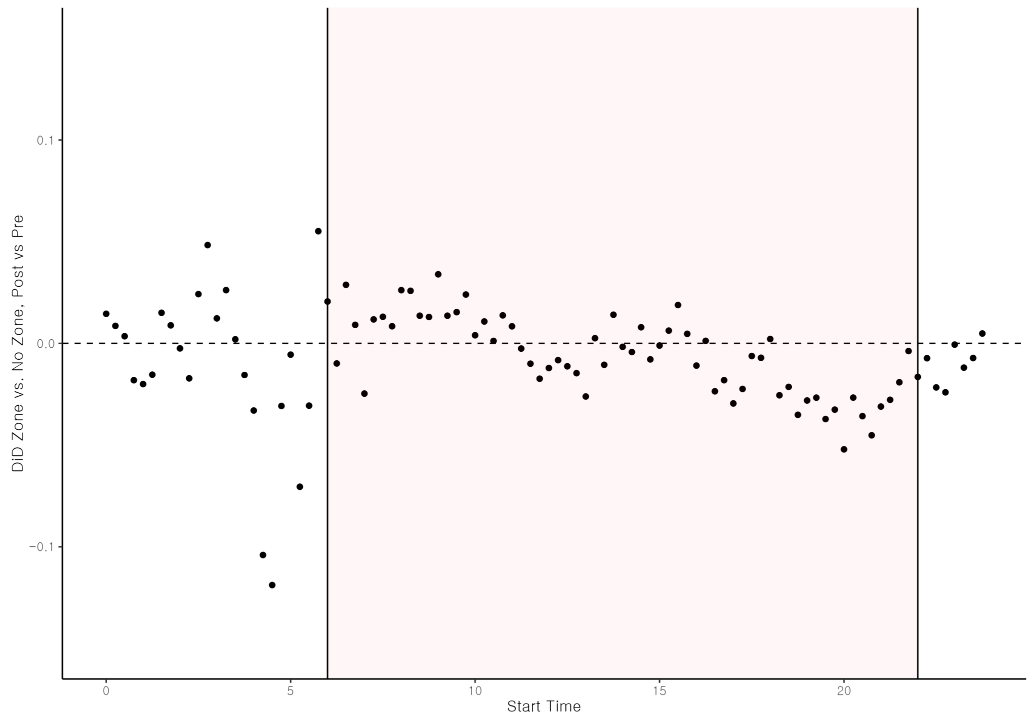
This figure provides a visual depiction of the triple differences estimator used to estimate the pass-through of the ridesharing tax. Each point in the Figure plots a difference in differences for a given 15-minute interval of the day. The first difference compares trips that use the downtown surcharge zone to those that don't use the downtown surcharge zone. The second difference compares is pre policy vs. post policy. The third difference compares peak and off-peak hours —– the downtown surcharge zone only applies between the hours of 6 am and 10 pm. This difference is the vertical distance between points inside and outside of the red shaded region. The blue dotted line at \$0.13 is the difference in the tax rate.

Figure 12 — Change in Ridesharing Tips



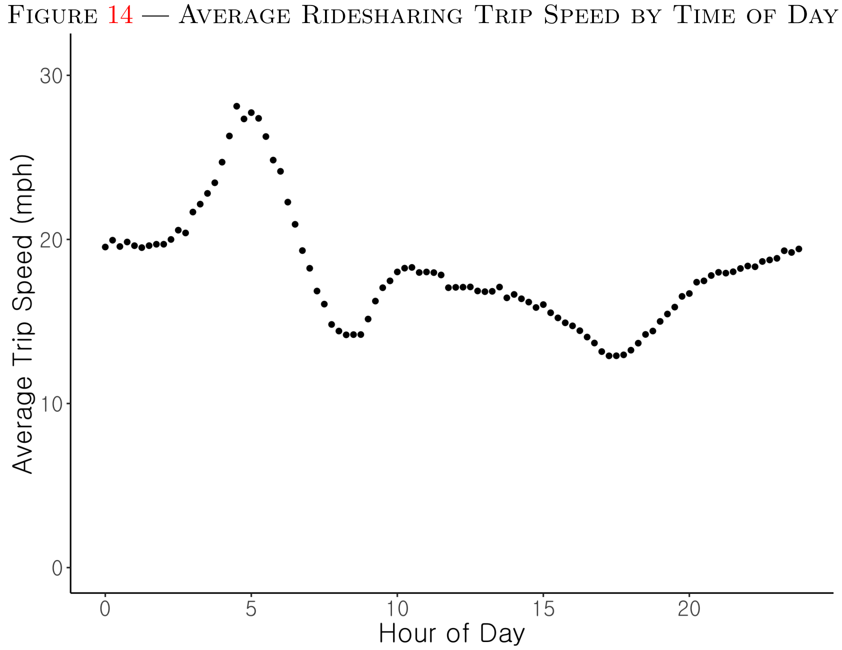
This figure provides a visual depiction of the triple differences estimator used to estimate the change in tips received by ridesharing drivers. Each point in the Figure plots a difference in differences for a given 15-minute interval of the day. The first difference compares trips that use the downtown surcharge zone to those that don't use the downtown surcharge zone. The second difference compares is pre policy vs. post policy. The third difference compares peak and off-peak hours —– the downtown surcharge zone only applies between the hours of 6 am and 10 pm. This difference is the vertical distance between points inside and outside of the red shaded region. The blue dotted line at \$1.75 is the change in the tax rate.

Figure 13 — Change in Ridesharing Tip Rate



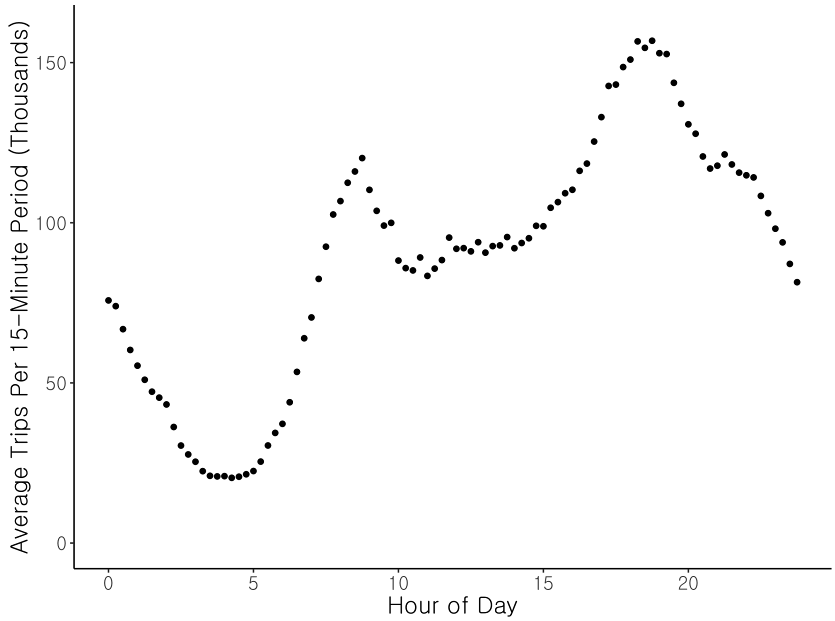
This plots the the difference in differences in tip rate for trips that do and do not use the surcharge zone, before versus after the GTT was implemented. The third difference is between peak (pink) and off-peak (white) hours.

Figure 14 — Average Ridesharing Trip Speed by Time of Day



This figure plots the average ridesharing trip speed for the city of Chicago between November 15$^{\text{th}}$ and February 20$^{\text{th}}$ for the years of 2019 and 2020, according to data available through the *Chicago Open Data Portal*. The average speed was calculated by dividing the reported length of the trip by the reported duration. Note that while start and end times are rounded for privacy reasons, the trip duration is not rounded.

Figure 15 — Average Ridesharing Trips by Time of Day



This figure plots the average number of ridesharing trips reported in Chicago for each 15-minute period of day between November 15th and February 20th of 2019 and 2020. This figure reflects ridesharing trip data available through the *Chicago Open Data Portal*.

[Air Pollution Monitor Map Here]

[CEMS Facility Map Here]