The Impact of Ride-Sharing Taxes: Evidence from Chicago

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Abstract

This paper examines the effects of policies that target rising congestion through the taxation of ride-sharing platforms. I provide evidence from an asymmetric ride-sharing tax change in Chicago – the largest in the United States. I find significant substitution away from solo ride-sharing trips to pooled trips and taxis, and aggregate ride-sharing utilization decreased. Despite the decrease in the number of trips, congestion remained unchanged. Aggregate short-term supply remained unchanged. To increase diversion away from ride-sharing and taxi trips, taxes for solo ride-sharing trips need to be almost \$5 higher and taxis need to incur a \$1 tax.
JEL: L92, L98, R48

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1. Introduction

Ride-sharing has become ubiquitous, easily surpassing the market share of traditional taxis. Utilization has largely been concentrated in dense metropolitan areas, likely driven by platforms' strategic entry decisions. Simultaneously, congestion has been rapidly increasing. Governments have attempted to combat rising congestion with driving restrictions, investment in public transportation, and various forms of road pricing. Recently, cities have blamed the entry of ride-sharing platforms for their congestion problems and have targeted these platforms with new policies. Many large cities have proposed or passed such policies: Seattle increased per-trip ride-sharing taxes

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by about \$0.50, San Francisco proposed a new 3.25% tax on solo trips and 1.5% tax on pooled trips, New York City imposes per-trip taxes of \$2.75 for solo trips and \$0.75 for pooled trips, and Washington D.C. has recently proposed a \$2 increase in per-trip taxes on ride-sharing trips, among many others. Yet another example is Chicago: the largest ride-sharing tax change in the United States was implemented in the city in early 2020. Recognizing that some types of ride-sharing trips induce more congestion than others, the city introduced asymmetry in the tax hike. Solo trips in downtown areas experienced a much larger increase than pooled or suburban trips. This paper documents the effects of the policy, estimates a flexible model of demand to evaluate welfare, and, based on the model, considers alternative policies to reduce congestion.

The tax aimed to reduce congestion, induce substitution to pooled trips, and generate revenue to invest in public transit. The new policy raised taxes on weekday trips during heavy traffic hours. The city raised taxes more heavily in downtown areas than in suburban areas. Ride-sharing products were affected differentially: solo trips were taxed more heavily than pooled trips while taxes on other modes of transportation remained unchanged.[2] The tiered structure of the tax provides spatial and temporal variation to evaluate the impact of the new policy. The analysis relies on the universe of ride-sharing trips collected by the City of Chicago. Each observation in the data is a trip with an associated cost (i.e., fare, tip, and additional charges), duration in seconds, distance in miles, pick-up and drop-off locations, and the number of other rides with which the trip was pooled. I augment the data with several other sources, including a similar database of taxi trips in Chicago and SafeGraph population flows as a measure of market sizes.

I use difference-in-differences to show changes in substitution patterns, congestion, and labor supply decisions after the tax was implemented. The share of pooled rides within ride-sharing services surged by 1.1% and the share of taxis (conditional on taking either a taxi or using a ride-sharing platform) increased by 1.4%. That is, a large portion of individuals switched from solo trips to pooled and taxi trips. Many consumers also substituted away from ride-sharing altogether: aggregate utilization of ride-sharing services decreased, suggesting that consumers switched to the outside option of private

[2]More details on the tax can be found on the City of Chicago's website. Additional information is provided in Section 2.2.

vehicles, public transportation, or walking. Despite the decrease in vehicle utilization, congestion was largely unaffected by the policy. One explanation is idle drivers; if the same number of drivers remain on the road without passengers, congestion should remain unchanged. Difference-in-differences reveal that the total number of drivers for ride-sharing platforms did not decrease and neither did the number of trips per driver. Taken together with the utilization and congestion results, ride-sharing drivers likely remain idle on the road and thus still contribute to congestion.

Motivated by the preceding empirical evidence, I developed a model of demand and back-of-the-envelope calculations for supply-side objects. A nested logit specification yields estimates that consumer welfare decreased approximately \$200,000 per day, most of which is concentrated during evening commute times. Supply-side calculations suggest modest increases in taxi profits, decreases in platform profits and driver surplus (especially for multihoming drivers), and significant gains in government revenue. On the whole, the total surplus increased.

Counterfactual simulations compute potential tax changes to achieve diversion to congestion-reducing modes of transportation. In particular, I consider targets for changes in (i) the share of taxis, (ii) the share of pooled rides, and (iii) the share of inside goods. The counterfactual policies suggest that much higher tax schedules are needed to reduce congestion as they far exceed the implemented changes while not demanding much additional diversion. To induce double the diversion to the outside option – assumed to be less congesting modes of transportation – the tax on solo ride-sharing trips needs to be \$4.68 higher in downtown areas and taxis need to incur a tax of approximately \$1 per trip. This is a substantial deviation from the implemented policy and results in significant additional losses to consumer surplus, suggesting that a ride-sharing tax is not the optimal way to reduce congestion.

This study contributes to several strands of literature, the first of which is related to ride-sharing and taxi markets. These markets have been the subject of a burgeoning literature over the last decade. For example, various studies have examined the allocative efficiency of drivers and riders and welfare effects of surge pricing, such as Buchholz (2022), Fréchette et al. (2019), Cohen et al. (2016), and Castillo (2022). In a similar vein, others study decentralization (Gaineddenova (2022)), platform competition (Rosaia (2023)), and externalities – such as traffic fatalities and congestion – induced by ride-sharing (Anderson and Davis (2023) and Li et al. (2022)). I complement these studies by developing a structural model of demand with a wide set of differentiated choices of transportation mode and analyses of counterfactual policies targeted for congestion reduction.

Additionally, this paper is related to the literature on the passthrough of taxes. As noted in Leccese (2024), many empirical studies have provided evidence of heterogeneity in the passthrough of taxes (Besley and Rosen (1999), Kenkel (2005), and Doyle and Samphantharak (2008)) and others have examined passthrough in related industries (Shapiro (2018) and Farronato and Fradkin (2022)). The theory on passthrough has largely focused on symmetric taxes (Weyl and Fabinger (2013)) with recent empirical extensions (Leccese (2024)). This study extends the theory for nested logit demand and asymmetric taxes where discrete tax changes can vary by product.

A final set of related literature is transportation policy. An increasing number of papers have evaluated the effects of public transportation subsidies and expansions (Bento et al. (2005), Parry and Small (2009), Duranton and Turner (2011), Anderson (2014), Basso and Silva (2014), Yang et al. (2018), and Gu et al. (2021)) while others examine driving restrictions (Davis (2008), Viard and Fu (2015), Zhang et al. (2017), and Jerch et al. (2021)). A large number of studies have additionally focused on explicit congestion pricing (Langer and Winston (2008), Anas and Lindsey (2011), Hall (2018), Yang et al. (2020), Kreindler (2018), and Mattia (2023)), and gasoline and electric vehicle taxes (Parry and Small (2005), Bento et al. (2009), Li et al. (2014), and Davis and Sallee (2020)). Some papers have focused specifically on Chicago (Liang et al. (2023), Zheng et al. (2023), Leccese (2021), Leccese (2024), and Almagro et al. (2023)). I contribute to research on transportation policy by evaluating a new type of policy – taxation of ride-sharing platforms – with a flexible model of demand and heuristic supply-side responses. I use the model to generate policies that target substitution to low-congestion modes of transportation, thus contributing to the policy debate on congestion pricing.

The remainder of the paper is organized as follows. Section 2 provides background on ride-sharing and taxi pricing strategies. Section 3 introduces the data and key variable construction along with summary statistics. Section 4 describes the empirical strategy and results. Section 5 and Section 6 develop the structural model and provide counterfactuals, respectively. Finally, Section 7 briefly concludes.

2. Background

2.1. Platform and Taxi Pricing

In contrast to taxis, platforms such as Uber and Lyft use algorithmic pricing to set trip fares.[3] Once a user opens the ride-sharing application and enters a dropoff destination, they will see different trip options with their corresponding estimated fares and durations. Trip fares are broken down into three parts: fare, local tolls and service fees, and tips. Local tolls are administratively set by city governments depending on the location of the trip. Importantly, these tolls include taxes, such as Chicago's ride-sharing tax, and are passed directly through to the rider. Service fees are flat charges set by platforms that vary by region. Tips are endogenously chosen by the rider either during or after the ride. The main component of the trip price is the fare that platforms set.

The algorithms to set fares differ by platform but are generally composed of a few important segments: a base fare, the type of ride (e.g., UberX, UberXL, UberPool, etc.), distance in miles, duration in minutes, and surge multipliers. Surge multipliers are influenced by the time of day, traffic, and driver availability. Notably, the upfront price that is shown to the rider is not always the price that they are charged. If there is a delay in requesting the ride, a destination is added, or the trip takes longer than estimated, a rider may face a higher fare.[4]

Platforms pay drivers based on similar algorithms. Drivers earn a base fare and earn additional income based on the time and distance traveled, where rates vary by city.[5] This works out to a proportion of the fare going to drivers. For example, in Houston, the market studied by Castillo (2022), the average commission rate for Uber drivers is 26.3%. For the purposes of this analysis, I take taxi pricing behavior as given. Taxis are subject to strict regulations on fare calculations and labor force participation in the purchase of a medallion.

[3] Details on Uber's algorithm can be found on their website.

[4] More details on surge pricing can be found in Castillo (2022).

[5] Recently, in some cities, drivers earn upfront fares in which case they see their earnings prior to accepting a trip. A similar program exists for riders. I abstract from upfront pricing given its recent implementation.

Table 1: Chicago's Ride-sharing Tax

Solo Ride	Original Tax	Updated Tax	w/ Surcharge
Standard	\$0.72	\$1.25	\$3.00
		+\$0.53	+\$2.28
Special Zone	\$5.72	\$6.25	\$8.00
		+\$0.53	+\$2.28
Pooled Ride	Original Tax	Updated Tax	w/ Surcharge
Standard	\$0.72	\$0.65	\$1.25
		-\$0.07	+\$0.53
Special Zone	\$5.72	\$5.65	\$6.25
		-\$0.07	+\$0.53

Notes: The table provides a description of the ride-sharing tax implemented by Chicago for solo and pooled trips. The second column describes the original tax (before January 6, 2020). The last two columns show the updated tax without and with a downtown surcharge, respectively (after January 6, 2020). Tax changes relative to the original tax are shown below (plus for an increase and minus for a decrease).

Source: The City of Chicago's website.

2.2. Chicago's Ride-sharing Tax

In an effort to curb congestion, Chicago is one of a few cities to implement an extra tax on ride-sharing services. There is a tiered structure to the new tax. It relies on several ride characteristics including if the ride is pooled, starts or ends downtown or in a special zone, or is in a wheelchair-accessible vehicle (WAV). I use the term "high-tax" to refer to geographic areas that are subject to a higher updated tax with a downtown surcharge. Similarly, I use the term "low-tax" to refer to geographic areas that are not subject to the downtown surcharge. Table 1 provides a comparison of the original and updated tax on ride-sharing platforms.

The goal of the tax is to reduce the number of vehicles on the road and to encourage utilization of pooled rides within ride-sharing services while also generating more revenue for the city. The government targeted downtown areas of the city for higher tax hikes, as presented in Figure 1. The tax was announced several months in advance so there is concern about the actual treatment date. However, the effects of the announcement do not appear to be salient upon comparing trends in trips from the previous year.

At first glance, the tax had a significant effect on ride-sharing fares, shown in Figure C1. The figure breaks down the impact of the tax by two dimen-

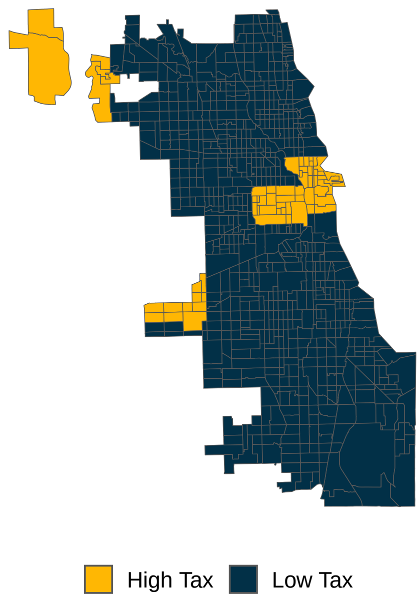

Figure 1: Map of Ride-sharing Tax

Notes: The figure presents a map of high-tax and low-tax areas after the implementation of the ride-sharing tax in Chicago. The gold regions are high-tax, i.e., areas with a surcharge, and the blue regions are low-tax, i.e., areas without a surcharge.

sions: geographic area (high-tax versus low-tax) and type of trip (solo versus pooled). Fares spiked after the tax increase, especially for solo trips in high-tax areas. The effects are far less pronounced in all other panels, suggesting that platforms passed through a much smaller portion of the tax for trip types that they would likely lose to alternate forms of transportation.

3. Data

3.1. Sources

The main data sources are the universe of ride-sharing and taxi trips in Chicago and daily mobility patterns from SafeGraph. Additional sources include daily weather reports near Chicago from the National Weather Service and hourly traffic accidents collected by the city of Chicago.[6]

3.1.1. Chicago Open Data Portal

The analysis leverages trip-level data covering the universe of ride-sharing trips in Chicago. I select two samples: December 2018 through January 2019 and December 2019 through January 2020. The four months of data encapsulate more than 30 million trips on ride-sharing platforms. Subsequent data is not included because the pandemic distorted ride-sharing utilization.

Each observation contains a number of useful variables related to prices, 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. Additional charges, including tax, are not rounded. 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, and 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 Census tract and community area of the ride. Each community area in Chicago is roughly a few square miles.

[6] The Chicago Open Data Portal has many searchable data sources on their website, aggregate Safegraph data is included on Github, and the National Weather Service constructs downloadable data available by request from their website.

The data is augmented with an analogous trip-level taxi dataset, ride-sharing platform driver registration. The taxi data includes the same variables of interest as well as a car identifier. The platform driver registration is recorded at a monthly level and includes the state, city, and Zip code of each driver's home, as well as monthly trip totals and an indicator for whether the driver multihomes (i.e., drives for multiple platforms).

3.1.2. SafeGraph

The SafeGraph data measures origin-destination population flows via anonymous mobile phone users' visit trajectories. Public data is available in various forms of granularity thanks to Kang et al. (2020); I rely on daily data collected for directed Census tract endpoint pairs. I select population flows that only occur within the Census tracts for Chicago in the analysis sample, which account for approximately 8 million observations. In order to allow hourly analysis, I assume that population flows follow the same hourly distribution by day of the week as ride-sharing and taxi trips. I spread daily population flows over hours according to these distributions which are presented in Figure B1. I also scale SafeGraph population flows by a factor of twenty-five in order to account for the small sample of phones in the data.

3.1.3. Additional Data

The analysis is further augmented with Zip code median income from the American Community Survey, hourly traffic accident reports from the Chicago Open Data Portal, and daily weather reports from numerous stations surrounding Chicago from the National Weather Service.

3.2. Variable Construction

The analysis relies on several important data constructs. First, I match traffic accidents' latitude-longitude coordinates to community area shape files. I also determine the nearest weather station to join the relevant precipitation and snow data. To do so, I proxy for community area location with its centroid and use Haversine greater-circle distance to find the closest station.

Congestion is a key outcome variable. I operationalize congestion as the speed of taxis in miles per hour. I choose taxi speeds because the composition of ride-sharing trips affects the average speed but is endogenous to the tax change. Additionally, I include indicators for days of the week, hours, and whether the trip was subject to a surcharge at either endpoint. All weekend

Table 2: Summary Statistics

	Fare	Miles	Minutes	MPH	Taxes	Daily	N
TNP Trips	10.17	4.93	22.78	16.30	3.29	216,518	8.44M
	(6.94)	(4.84)	(16.76)	(8.34)	(1.96)	(37,170)	
Solo	10.24	4.58	22.79	15.70	3.52	195,672	7.63M
	(7.08)	(4.64)	(16.79)	(7.47)	(1.86)	(34,388)	
Pooled	9.60	8.17	22.75	21.90	1.10	20,845	0.81M
	(5.36)	(5.49)	(16.59)	(12.73)	(1.46)	(3,778)	
Taxi Trips	13.70	3.43	14.20	12.19	0.66	31,944	1.25M
	(63.16)	(5.02)	(20.89)	(8.36)	(10.51)	(7,100)	

Notes: The table provides summary statistics for TNP trips (i.e., rides taken on platforms such as Uber and Lyft) and taxi trips. Simple averages are presented for several covariates. Daily refers to the average number of trips taken on a given day. The numbers in parentheses are standard deviations.

and holiday trips are omitted from the sample. I also remove trips before 6:00am and after 10:00pm because these trips are unaffected by the tax and more sparse than day-time trips. Markets are defined as directed community area endpoints and hourly time-of-trip.

3.3. Descriptive Statistics

Table 2 reports descriptive statistics on the count, length, fare, and make-up of ride-sharing and taxi trips. Unsurprisingly, solo trips are shorter and more expensive per-mile than pooled trips. Pooled trips account for about 7% of the sample and have much lower taxes. Taxis are the final trip type included in the data, accounting for almost 10% of the data. Taxi trips are, on average, shorter and the most expensive in terms of per-mile fare. They are also subject to the lowest tax rate. A per-trip tax change is the key source of variation I exploit in this paper; Figure C1 confirms the presence of the tax discontinuity.

4. Evaluating the Ride-Sharing Tax

4.1. Substitution, Congestion, and Utilization

The primary empirical method is difference-in-differences. Given that all geographic areas are affected by a tax change in the treatment period, I include the previous year of data as a control group. The key idea is to compare the same areas on the same dates, conditioning on where congestion is measured. Thus, any changes in congestion will be those induced by the change in the composition of trips driven by the tax. The estimating equation is given by:

$$\bar{y}_{it} = \alpha_i + \gamma_{w(t)} + \beta \text{Treatment}_{it} + \eta \text{Post}_{it} + \theta D_{it} + \varepsilon_{it} \tag{1}$$

Origin-destination pairs (markets) are indexed by i and days are indexed by t. I include day-of-the-week fixed effects in $\gamma_{w(t)}$ and market fixed effects in α_i. Treatment is an indicator for the observation belonging to the treatment group and Post is an indicator for the observation being after January 6th of its respective year. The treatment group is the sample from December 2019 to January 2020 and the control group is the sample from December 2018 to January 2019. The variable D is an interaction of Treatment and Post. The response $\bar{y}_{it}$ is the relevant outcome, e.g., the share of pooled trips in a given market.[7]

The first set of results examines the impact of the tax on substitution patterns across modes of transportation, congestion, and utilization. The results in this section focus on high-tax areas because the treatment effects are driven primarily by high-tax areas. The results for low-tax areas can be found in Table C1, Table C2, Table C3, and Table C4.

Figure 2 shows that consumers switch from solo to pooled trips, conditional on taking a ride-sharing trip. The jump is especially sharp in high-tax areas where the tax on solo trips increased significantly more than the tax on pooled trips; the regressions focus on these areas.[8] The regressions in Table 3 present the results of the difference-in-differences. The first column reveals that the share of pooled rides (conditional on choosing a ride-sharing platform) increased by 1.1 percent in high-tax areas. This is consistent with Figure 2 where there is a significant jump in the share of pooled trips. Consumers switch to pooled trips – a less congesting mode of transportation. However, this does not necessarily imply that congestion improved.

Next, Figure 3 shows substitution from ride-sharing to taxis, conditional on choosing an inside good (either ride-sharing or taxis as a mode of trans-

[7] A threat to identification is the consumer's choice to shift the time of their rides slightly early to avoid the tax or to move just outside of the taxed area to request a ride. Appendix B.4 argues that this is not empirically relevant.

[8] Given the sharpness of the discontinuity, any concerns about the pre-announcement of the tax are alleviated.

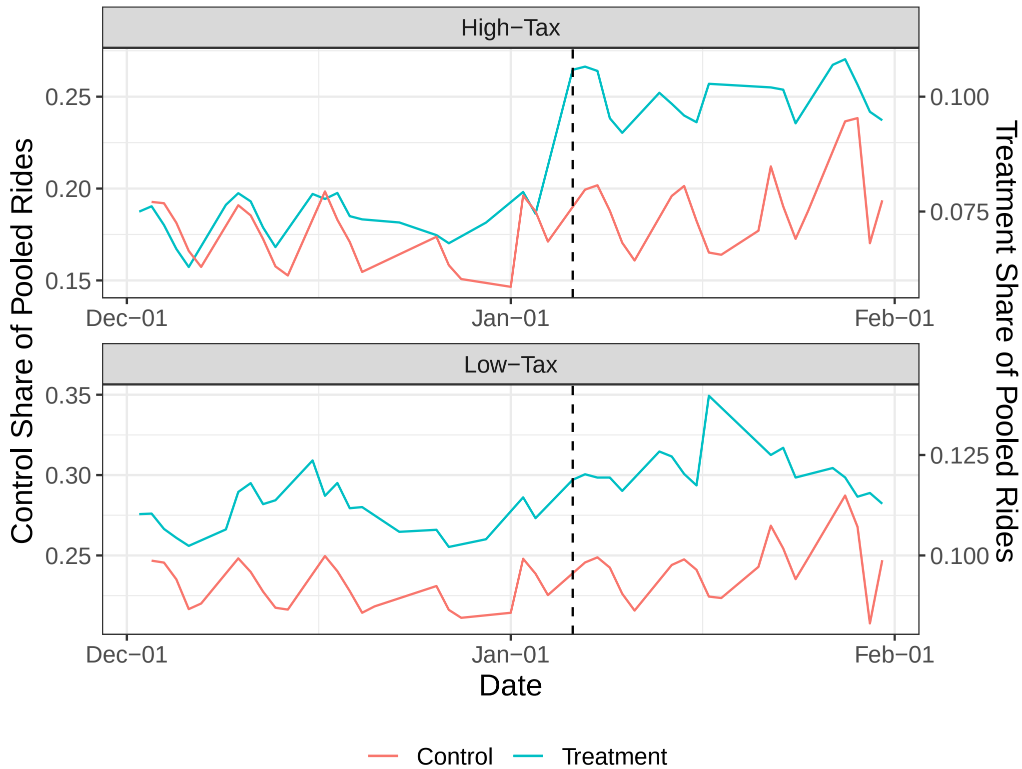

Figure 2: Ride-share Composition

Notes: The figure presents trends in the conditional shares of solo and pooled trips on ride-sharing platforms. High Tax and Low Tax refer to areas with and without a surcharge, respectively. The control group (red) is the previous year of data and the treatment group (blue) is the more recent year that was affected by the tax change.

Table 3: Substitution, Utilization, and Congestion Induced by the Tax

	Dependent variable:					
	Substitution and Congestion			Number of Trips		
	Pooled Share	Taxi Share	Log MPH	Solo	Pooled	Taxi
Post	0.015***	-0.029***	0.033**	0.938	4.053***	-9.966**
	(0.001)	(0.004)	(0.004)	(1.762)	(0.566)	(3.200)
Treatment	-0.097***	-0.024***	-0.016***	32.114***	-21.533***	-9.046**
	(0.006)	(0.004)	(0.005)	(3.863)	(2.355)	(3.099)
Treatment × Post	0.011***	0.019***	0.004	-17.047***	1.014*	2.943*
	(0.001)	(0.004)	(0.006)	(3.836)	(0.401)	(1.181)
Obs.	56,112	135,054	34,944	55,133	44,966	34,955
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.840	0.114	0.936	0.949	0.816	0.887

Notes: The table presents results from the difference-in-differences specification for the share of pooled rides, the share of taxis, and log miles per hour in high-tax areas. The specifications include origin-destination pair fixed effects and day-of-week fixed effects. Standard errors are clustered by market. *p<0.1; **p<0.05; ***p<0.01

portation). The second column of Table 3 shows that the share of taxis increased by 1.9 percent in high-tax areas. The last three columns in Table 3 show that aggregate utilization of solo trips decreased and the increase in taxi and pooled trips was not enough to make up the difference. The difference-in-differences estimates presented in the third column of Table 3 show no significant effect of the tax on congestion. Despite the significant substitution away from solo trips and the decrease in utilization, on the whole, congestion remains unaffected.

Taken together, the results suggest several mechanisms by which congestion remains unchanged. First, ride-sharing drivers, although picking up a larger fraction of pooled riders than solo riders, remain idle and thus still contribute to congestion. Second, the riders induced to choose the outside option may have mostly chosen personal vehicles or other congestion-inducing modes of transportation.[9]

4.2. Labor Supply

I examine driver registration data to measure labor supply responses to the tax. Any short-term labor supply response would point to differences between the two mechanisms described above. The data is limited: I observe the monthly number of trips per driver without a driver identifier. I bin drivers into coarse categories based on the month they started driving and their home location variables, which are recorded down to a Zip code.[10] A control group is constructed from the previous year. The estimating equation is a difference-in-differences:

$$\log(n_{it}) = \alpha_L + \gamma_M + \beta \text{Treatment}_{it} + \eta \text{Post}_{it} + \theta D_{it} [+\lambda \text{Multihomes}_{it}] + \varepsilon_{it} \quad (2)$$

I include fixed effects for driver characteristics, such as the starting month γ_M and location α_L. The response variables considered are the log number of

[9] Recent survey responses suggest that a significant portion of households in Chicago – especially in high-tax areas – do not own vehicles, meaning this is not a viable option. An article in Chicago Magazine from 2014 describes the survey in which there are pockets of the city with 60-70% of households that do not own a vehicle. Further, according to the Office of the Illinois Secretary of State, annual county vehicle registration counts have been decreasing. Between 2018-2020, vehicle registrations decreased from 2.23M to 2.07M while the population increased from 5.17M to 5.26M in the same period according to FRED.

[10] I uniquely identify about 60% of the registered drivers in the data using these bins. For almost 90% of the data, I have at most five drivers in a bin.

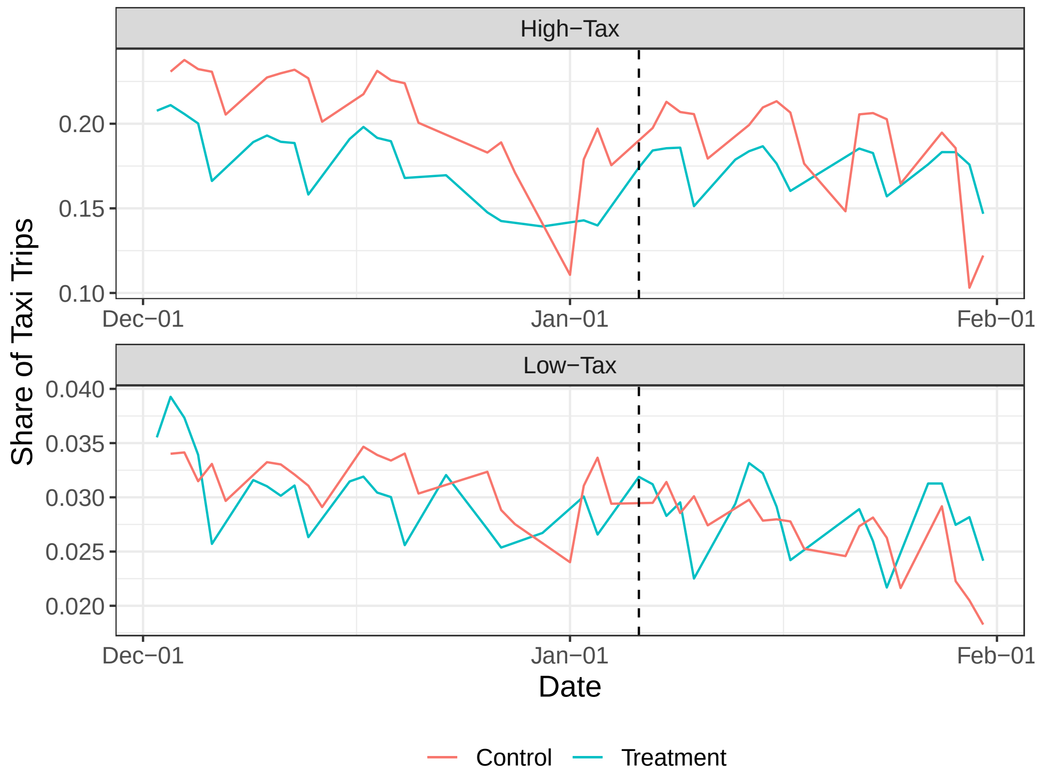

Figure 3: Taxi Composition

Notes: The figure presents trends in the share of taxi trips. High Tax and Low Tax refer to areas with and without a surcharge, respectively. The control group (red) is the previous year of data and the treatment group (blue) is the more recent year that was affected by the tax change.

drivers and the log number of trips per driver, denoted $\log(n_{it})$, in a given bin i. Bins are composed of location and starting month in a tuple $i = (L, M)$. The coefficient θ is the labor supply response to the policy change. Separate regressions are included for drivers who multi-home, i.e., those who drive for both Uber and Lyft. In the "aggregate" regression which includes all types of trips, I include the share of multihoming drivers of a particular type i, which is denoted by Multihomes. This variable is only included in the aggregate regression.

Table 4 presents the results of the difference-in-differences. The first column shows that the aggregate short-term labor supply of drivers did not meaningfully respond to the tax. This result is consistent with the fact that congestion remained largely unchanged: the number of ride-sharing drivers remains stable despite the significant changes in substitution and utilization after the tax. The third column looks at the intensive margin of drivers' decisions in the number of trips per driver. Consistent with the extensive margin in the first column, trips per driver do not meaningfully respond to the tax change.

I also break down the analysis into drivers who multihome — those who drive for both Uber and Lyft — and those who drive for a single platform in the second and third columns, respectively. The coefficients suggest that the effects of the tax are far more salient for those who multihome. The labor supply decreases by 3.9 percent for these drivers whereas there is not a statistically significant result for those who drive for a single platform.[11] Most drivers single-home which is still consistent with the lack of changes in congestion.[12] The intensive margin in the fifth and sixth columns again matches in the extensive margin: single-homing drivers are not driving more trips but multi-homing drivers decrease their trip counts.

4.3. Tax Passthrough

Passthrough of the tax is estimated as the change in fare after the new policy went into effect. For example, if the fare increased by the same amount

[11] One explanation for this result is an income effect wherein drivers who multihome are more reliant on driving as a primary income source and are thus more likely to switch to another form of income. The results for a triple differences specification are presented in Table B1.

[12] More than two-thirds of drivers with one or more trips during the sample period single-home.

Table 4: Percentage Change in Platform Labor Supply

	Dependent variable:					
	Log Number of Drivers			Log Trips per Driver		
	Agg.	Single	Multi	Agg.	Single	Multi
Post	-0.020***	-0.038***	-0.005	-0.021*	-0.044**	-0.001
	(0.006)	(0.008)	(0.007)	(0.012)	(0.017)	(0.017)
Treatment	-0.266***	-0.462***	-0.120***	-0.011	-0.052**	0.010
	(0.006)	(0.009)	(0.007)	(0.012)	(0.018)	(0.017)
Treatment × Post	-0.014*	0.019*	-0.039***	-0.023	0.015	-0.069**
	(0.008)	(0.012)	(0.009)	(0.016)	(0.023)	(0.023)
Multihome	-0.200***			0.313***		
	(0.004)			(0.009)		
Obs.	92,064	50,361	41,703	92,064	50,361	41,703
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Start Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.594	0.638	0.575	0.298	0.334	0.308

Notes: The table presents results from the difference-in-differences specification for ride-share labor supply. Agg. is a regression that bins all types of drivers together. Single refers to drivers who only drive for one platform (e.g., only Uber) and Multi refers to drivers who drive for multiple platforms. Fixed effects include the driver's home Zip code and starting month. *p<0.1; **p<0.05; ***p<0.01

Table 5: Ride-Sharing Platform Passthrough of the Tax

	Dependent variable	
	Base Fare	
	Solo	Pooled
Post	-2.223***	-0.367***
	(0.013)	(0.012)
Treated	-0.009	824***
	(0.049)	(0.033)
Treated × Post	1.663***	0.157***
	(0.033)	(0.024)
Passthrough	0.729	0.296
Obs.	55,133	44,966
Market FE	Yes	Yes
Weekday FE	Yes	Yes
Adj. R^2	0.995	0.966

Notes: The table presents results from the difference-in-differences specification for passthrough in high-tax areas. The specifications include origin-destination pair fixed effects and day-of-week fixed effects. Passthrough is measured as $\frac{\theta_j}{\Delta\tau_j}$ where θ_j is the coefficient on Treated × Post for product j and $\Delta\tau_j$ is the discrete tax change for the product. A product is either a solo trip or a pooled trip. Standard errors are clustered by market. *p<0.1; **p<0.05; ***p<0.01

as the tax then there is perfect passthrough. Likewise, if the fare was unaffected then there is zero passthrough.

$$\text{Fare}_{it} = \alpha_i + \gamma_{w(t)} + \beta\text{Treatment}_{it} + \eta\text{Post}_{it} + \theta D_{it} + \Lambda\mathbf{X}_{it} + \varepsilon_{it} \tag{3}$$

The notation for the variables remains the same as the difference-in-differences specification above. I also include additional controls **X** which is a vector of miles and duration in seconds of the trip. Passthrough is then calculated as $\frac{\theta}{\Delta\tau}$ where $\Delta\tau$ is the relevant discrete change in the tax which can vary by product. The regression is estimated separately for solo and pooled trips in high-tax areas.

The results for the passthrough analysis are presented in Table 5.[13] The

[13]Disaggregated results can be found in Table C6.

difference-in-differences specifications suggest that approximately 73 percent of the tax on solo trips and 30 percent of the tax on pooled trips is passed through to the consumers by ride-sharing platforms.[14] Intuitively, consumers who choose pooled trips are likely more price-sensitive than those who choose solo trips. The ride-sharing platforms should pass through less of the tax hike to the more elastic consumers and must internalize some substitution between solo and pooled trips.

5. Model

5.1. Demand

The model of demand closely follows Berry et al. (1995). Each market is defined by an origin-destination-time pair, summarized by an index t. Products are denoted $j \in \mathcal{J}_t$ where a product is a solo trip, pooled trip, or taxi trip. These products can belong to nests indexed by $g \in \mathcal{G}$. All other modes are collapsed into the outside option. The indirect utility of consumer i in market t from choosing product j in nest g is given by:

$$u_{ijt} = \underbrace{\mathbf{X}_{jt}'\beta - \alpha p_{jt}(\tau_{jt}) + \xi_{jt}}_{\delta_{jt}} + \zeta_{igt} + (1-\rho)\varepsilon_{ijt} \tag{4}$$

Here, I define $\mathbf{X}_{jt}$ as a vector of product characteristics and p_{jt} as the price of product j in market t. The price is left as a function of the tax rate τ_{jt} on product j in market t. Additionally, I decompose $\xi_{jt} = \xi_j + \xi_t + \tilde{\xi}_{jt}$ into product fixed effects ξ_j, hour and weekday fixed effects ξ_t, and unobserved market-specific shock to the utility of product j denoted by $\tilde{\xi}_{jt}$. Closing the model, the outside option — private vehicle, public transportation, walking, or other unmeasured modes — is defined as $j = 0$ in each market with mean utility normalized to zero. The shocks ε_{ijt} are assumed to be i.i.d. T1EV with ζ_{igt} such that the term $\zeta_{igt} + (1-\rho)\varepsilon_{ijt}$ is also distributed T1EV for any $\rho \in (0, 1)$.

Under the assumption that consumers choose a product to maximize their utility and the distributional assumptions on the shocks, market shares are

[14] Table C6 presents the results for the low-tax areas of the city which experienced a smaller change in the tax – even a subsidy for pooled trips.

given by:

$$s_{jt} = \underbrace{\frac{\exp\left(\frac{\delta_{jt}}{1-\rho}\right)}{\sum_{j' \in \mathcal{J}_{g(j)t}} \exp\left(\frac{\delta_{j't}}{1-\rho}\right)}}_{\bar{s}_{j|g}} \underbrace{\frac{\left(\sum_{j' \in \mathcal{J}_{g(j)t}} \exp\left(\frac{\delta_{j't}}{1-\rho}\right)\right)^{1-\rho}}{\sum_{g'} \left(\sum_{j' \in \mathcal{J}_{g't}} \exp\left(\frac{\delta_{j't}}{1-\rho}\right)\right)^{1-\rho}}}_{\bar{s}_g} \tag{5}$$

Let $g(j)$ be the nest to which product j belongs and let g be a generic nest. I denote $\mathcal{J}_{g(j)t}$ as the set of products in nest $g(j)$ that are available in market t. Similarly, $\mathcal{J}_{gt}$ is the set of products in nest g that are available in market t. The term on the left $\bar{s}_{j|g}$ is the market share of product j conditional on its nest g. The term on the right $\bar{s}_g$ is the total market share of nest g.

5.2. Passthrough

I extend the theoretical results in Leccese (2024) with a set of first-order conditions in which market shares respond to discrete changes in taxes in a nested logit framework. I assume that the price of each good depends only on the tax for that good, prices are linear in taxes, and taxes only affect mean utilities through price changes. The change in consumer i's choice probability of product j under tax changes $\Delta\tau$ is given by:

$$\frac{\partial s_j}{\partial \tau} = \frac{\alpha}{1-\rho} s_j \left[\frac{\partial p_j}{\partial \tau_j} \Delta\tau_j - \rho \sum_{k \in g(j)} \frac{\partial p_k}{\partial \tau_k} \Delta\tau_k \bar{s}_{k|g} - (1-\rho) \sum_k \frac{\partial p_k}{\partial \tau_k} \Delta\tau_k s_k \right] \tag{6}$$

The terms in this expression are intuitive. The first term represents the shares diverted from the given product due to the tax change. The second term accounts for substitution within a given nest $g(j)$. The final term accounts for substitution across nests. For example, when $\rho \to 1$, all shares are diverted to $k \in g(j)$ and nothing moves to $k \notin g(j)$ due to perfect within-nest substitution. Notably, the passthrough conditions are the same as logit when $\rho \to 0$ or $g(j)$ includes all products and the outside option. I refer to these first-order conditions as "passthrough conditions" in the remainder of the text.

5.3. Instruments

I employ a battery of instruments to address the endogeneity of price and to estimate the nesting parameter. I use the classic instruments from Berry et al. (1995): number of rival products, average rival fare, average rival miles traveled, average rival duration in seconds, and average rival miles per hour. An indicator for the post-period is also included given the exogenous shock to prices through the asymmetric tax change.

I rely on additional instruments to provide more variation. First, I use weather as measured by many weather stations surrounding the city. Daily weather (such as precipitation and snow measurements) is recorded for both pickup and dropoff locations. I assume that weather does not directly enter the consumer's utility function. Instead, preferences for weather enter through the price. Ride-sharing platforms adjust prices based on shocks to demand due to inclement weather, meaning the price already reflects these additional preferences. However, although collected at various points throughout and around the city, these shocks are likely correlated across markets.

The final set of instruments I use are related to accidents. I collect hourly data on traffic accidents and match them to their corresponding community areas. The data include measures of severity with the number of vehicles involved in the accident, the number of injuries, and a dollarized value of the damage. The intuition behind this instrument is that accidents are unexpected and exogenously increase the time and mileage required to travel between two endpoints. This drives up the price of the ride-sharing trip because ride-sharing platforms adjust prices according to the time and mileage required for a trip.

5.4. Results

The preferred specification is nested logit with separate nests for platforms and taxis. Table 6 shows the results of demand estimation. Figure C5 depicts the mean own-price elasticities from the fourth model with a nest for platforms and taxis. The elasticities for solo trips line up with the literature (e.g., a range from -0.25 to -1.06 in Cohen et al. (2016)). Riders who take pooled trips are far more price-sensitive while riders who take taxi trips are less price-sensitive. This is intuitive because those who take taxi trips likely know the approximate price and have a strong taste for taxi trips.

6. Counterfactuals

The counterfactuals examine alternate tax schedules that aim to reduce congestion by targeting substitution to low-congestion modes of transporta-

Table 6: Demand Estimates

	No Type FE	Type FE	Inside Nest	Type Nests
Price	0.670***	-1.307***	-0.211***	-0.067*
	(0.098)	(0.152)	(0.019)	(0.008)
log(Miles)	-3.696***	11.538**	2.114***	0.793***
	(0.690)	(1.252)	(0.152)	(0.075)
ρ			0.657***	0.798***
			(0.020)	(0.010)
	Median Own-Price Elasticities			
Solo	9.832	-19.178	-3.346	-1.166
Pooled	6.727	-13.121	-4.327	-2.179
Taxi	12.052	-23.509	-3.804	-1.209
Nesting	None	None	Inside	Platform
Hour FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Type FE	No	Yes	Yes	Yes
Obs.	1.6M	1.6M	1.6M	1.6M
F-stat (p)	25.64	73.41	49.92	48.33
F-stat (ρ)	—	—	71.18	70.26

Notes: The table presents results from various demand specifications. The first two columns are standard logit and the second column includes fixed effects for the type of trip. The last two columns are nested logit where Inside nesting refers to an inside-outside nesting structure and Platform refers to a nest for solo and pooled ride-sharing trips separate from taxi trips. Standard errors are clustered by market and reported F-statistics are Sanderson-Windmeijer tests for weak identification. *p<0.1; **p<0.05; ***p<0.01

tion and diversion to the outside option. All counterfactuals are computed relative to the baseline tax period, i.e., the cohort of markets from December 2019. I compute average daily values by market, recalling the market definition as directed community area pairs, the day of the week, and the hour of the trip. I assume that the primitives of the model are invariant to policies.

6.1. Surplus Definitions

In this section, I define the surplus notions used in the counterfactuals. It is important to note that consumer surplus is a typical object from the demand system, but all supply-side objects are back-of-the-envelope to mitigate the complexity of two-sided market pricing problems and data limitations.

6.1.1. Consumer Surplus

The definition of consumer surplus follows the nested logit structure:

$$\mathrm{CS}_t = -\frac{1}{\alpha}\log\left(1+\sum_{g\in G}\exp\left((1-\rho)\log\left(\sum_{j\in g}\exp\left(\frac{\delta_{jt}}{1-\rho}\right)\right)\right)\right) \tag{7}$$

Note that this is an individual's consumer surplus. Changes in consumer surplus can be computed by modifying taxes (thus changing δ_{jt}) and comparing values to the baseline.

6.1.2. Platform and Taxi Profits

The supply side is a transportation pricing problem. Firms — taxis and ride-sharing platforms — set prices for solo and pooled rides. I assume there is a single platform due to data limitations. The platform's profit is given by:

$$\pi_j^F = \sum_{k\in\mathcal{J}_j} s_{jk}(\cdot)\left[(1-w_j)(1-\nu_j)(p_{jk}-\tau_{jk}) - I_{jk} - g_j\right] \tag{8}$$

There are several components of a firm's marginal cost. At the risk of overloading notation, define w_j as the proportion of the fare set by ride-sharing platforms given to the driver. This is calibrated to $w_j = 0.263$ for ride-sharing platforms and $w_j = 0$ for taxis. Further, define $\nu_j = 0.03$ for sales tax and credit card fees. Finally, let I_j be the insurance cost for ride-sharing platforms and g_j be the cost of gas for taxis.[15] These are calibrated

[15] Drivers on ride-sharing platforms are entirely responsible for gas costs and thus the gas cost enters driver surplus rather than platform profit.

to $I_{jk} = 0.30$ and $g_j = \bar{x}_j \times \eta \times \bar{\lambda}^{-1} \times \bar{c}$. The cost of gas is scaled to reflect miles driven ($\bar{x}_j$), the inverse faction of idle time ($\eta = 2$), fuel efficiency ($\bar{\lambda} = 24.2$), and the average price of gas ($\bar{c} = 2.609$).

Given the algorithmic pricing practices of platforms and regulations surrounding taxis, I assume the only decision firms make is the passthrough rate $\frac{\partial p_{jk}}{\partial \tau}$ which is estimated in the first stage. Namely, the supply side comes directly from objects that are either observed in the data or estimated in prior stages. It is important to note that a lot of platforms' strategic behaviors are assumed away in the counterfactuals and the calibration relies on back-of-the-envelope numbers.

6.1.3. Government Revenue

Government revenue is the total amount of taxes collected in any given market under any given tax structure:

$$G = \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{J}_j} s_{jk}(\cdot)\tau_{jk} \tag{9}$$

Taxes are allowed to vary by product and market.

6.2. Estimates

There are four relevant comparisons. First, I compare the new tax to the original tax in order to evaluate the effectiveness of the implemented policy. Next, I create counterfactuals to target specific objectives: (i) specific relative shares of platforms and taxis, (ii) specific shares of solo and pooled trips within ride-sharing, and (iii) specific reductions in the inside share.

Each of the last three counterfactuals has four potential policy types: (i) fully flexible tax tiers that vary by location and product, (ii) flexible tax tiers that vary only by product, (iii) flexible tax tiers only for ride-sharing that vary by location and product, and (iv) taxes for ride-sharing platform products that cannot vary by location. For the sake of brevity, I present the high-tax policies from the fully flexible counterfactuals and relegate the remaining results to Appendix C. It is important to note that these are not optimal policies and they are unlikely unique solutions to achieve their targets.[16] However, they represent policies to address the issue of congestion

[16]In the targeted policy counterfactuals, I use a sample of 114 markets that appear every hour and day in the data for the sake of computational complexity.

Table 7: Welfare Results

Policy	ΔCS	$\Delta\Pi^P$	$\Delta\Pi^T$	ΔG	ΔTS
Baseline	-199,415	-10,932	185	304,028	93,866
Taxi Target	-202,090	-14,943	2,037	346,997	132,001
Pooled Target	-268,782	-15,248	266	374,094	90,330
Diversion Target	-437,357	-20,024	-683	562,242	104,178

Notes: The table presents changes in welfare for consumers, platforms, and taxis. The last two columns present changes in government revenue and total surplus. The estimates are aggregated over hours and days and then normalized to a single day. The Taxi, Pooled, and Diversion Target counterfactuals refer to fully flexible counterfactuals in the first columns of Figure C9, Figure C10, and Figure C11, respectively.

given the empirical patterns after the quasi-experiment in Chicago's transportation ecosystem.

6.2.1. Baseline

A baseline comparison shows the impact of the current tax on ride-sharing platforms. Figure C6 shows diversion to the outside goods of personal vehicles, public transportation, and walking, among others, as a percentage change in aggregate utilization of the inside goods predicted by the model. There is significantly more substitution to outside options in high-tax areas where the discrete tax change was much larger.

Table 7 presents the welfare comparison of the initial tax (a flat \$0.72 per trip) and the implemented tax change. There is a significant loss in consumer welfare and platform profits. However, the gains in tax revenue exceed the sum of these losses, yielding positive changes in total surplus. The numbers for changes in platform profits and taxi profits deviate significantly from the estimates in Leccese (2024). However, the figures presented here align closely with the reduced form evidence on changes in utilization. For example, the daily average change in taxi utilization in high-tax areas is 2.9 with a market-level daily average of 74.7 taxi trips per day. The differences are likely driven by a combination of market size definitions and aggregation. I consider many different markets with different sizes while the previous study only considered two markets.

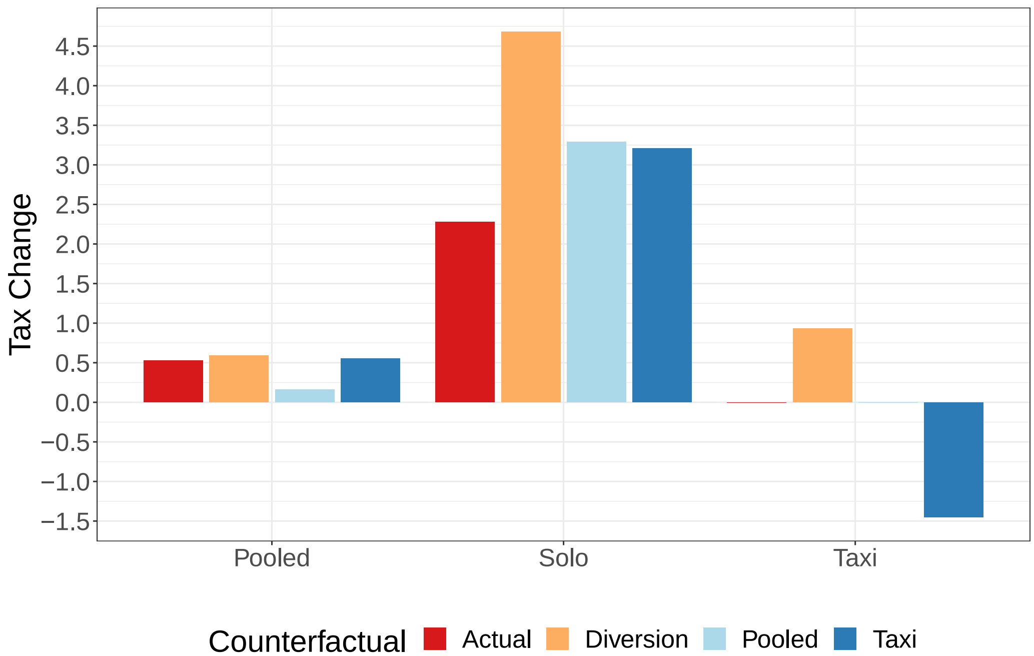

Figure 4: Counterfactuals

Notes: This figure represents potential changes in tax schedules (in dollars) that achieve different counterfactual goals: diversion to taxi trips, diversion to pooled trips, and diversion to the outside option. Each set of four bars is a mode (pooled, solo, and taxi). The four colors of bars represent different counterfactuals with the leftmost (red) being the implemented policy. The results presented are tax changes in high-tax areas.

6.2.2. Increase Taxi Shares

The first counterfactual targets the share of taxis to reduce congestion by deterring ride-sharing trips. Given that the number of taxi medallions is limited by cities, there is a fixed labor supply of taxis (in the short run), and thus their contribution to congestion is relatively fixed. Meanwhile, ride-sharing platforms provide dynamic incentives for drivers to provide their labor. This can greatly increase congestion by putting more drivers on the road. The model predicts a 1.4 percent increase in the conditional share of taxis after the implemented tax. I target a 3 percent increase in the share of taxis, double what the model predicts.

Figure 4 shows the change in tax schedule required to achieve a 3 percent increase in the share of taxis in the rightmost bars for each mode in dark blue. Intuitively, taxis are subsidized while ride-share trips are taxed, especially solo trips. The results show that, to induce such a change in the share of taxis, taxis in high-tax areas need to be subsidized by 1.5 dollars in conjunction with heavy taxes on ride-share trips in high-tax areas. The increases for solo trips are much higher than the realized tax changes at about \$4.6. Increases for pooled trips are more modest and similar to the tax change in reality at approximately \$0.6. The high tax changes are likely due to the large nesting parameter that indicates most substitution occurs within platform products.

6.2.3. Increase Pooled Shares

The second counterfactual targets the share of pooled rides to reduce congestion by deterring solo ride-sharing trips, which likely induce more congestion than pooled trips. The model predicts a 2.5 percent increase in the share of pooled trips after the implemented tax. I target a 5 percent increase in the share of pooled trips, double what the model predicts.

Figure 4 shows the change in tax schedule required to achieve a 5 percent increase in the share of pooled trips in light blue. Intuitively, solo trips are taxed heavily in high-tax areas, while taxes on pooled rides and taxis are largely unaffected. To induce this increase in the share of pooled trips, pooled rides in high-tax areas should not be taxed as high as the implemented policy with a tax increase of only about \$0.2. Meanwhile, solo trips need to be heavily taxed and taxis do not need to be taxed, which is intuitive given the strong correlation of within-platform choices. The taxes on solo trips are more similar to the realized tax change than the previous counterfactual. The increase required for solo trips in high-tax areas is \$3.29 while the realized increase was \$2.28.

6.2.4. Increase Diversion to the Outside Option

The third counterfactual targets the change in diversion to the outside option, i.e., the change in the inside share. Deterring all types of rides is a sure way to reduce congestion should the outside option include walking, biking, or public transportation. The model predicts an 8 percent decrease in the inside share after the implemented tax. I target a 15 percent decrease in the inside share, about double what the model predicts.

Figure 4 shows the change in tax schedule required to achieve a 15 percent decrease in the inside share with orange bars. Intuitively, all modes of transportation considered are taxed, especially solo trips. To induce this decrease in the inside share, solo trips need to be taxed heavily, pooled trips need to be taxed moderately, and taxis need to be taxed lightly. Taxis require a tax change of \$0.9 in high-tax areas. Tax changes for solo trips are the most extreme in this counterfactual, peaking at about \$4.7 compared to the change of \$2.28 that was implemented in practice. The counterfactual taxes for pooled trips are closer to the implemented tax with a tax increase of \$0.5.

7. Conclusion

Congestion is a salient issue and a hot topic of debate; the ubiquity of ride-sharing platforms has played a role in driving congestion issues. Many cities have considered implementing or have already implemented changes to address the problem. This study provides some of the first insights into Chicago's ride-sharing tax, one of the largest tax changes aimed at controlling congestion in the United States. The goals of the tax were to decrease congestion, increase the share of pooled trips on ride-sharing platforms, and fund investment in public transportation.

There are several important takeaways. Although the tax successfully diverted consumers away from solo ride-sharing trips to pooled trips, taxis, and the outside option, congestion was not significantly affected. Short-term labor supply did not meaningfully respond to the tax change. Motivated by the empirical evidence, a structural model of demand shows significant losses in consumer welfare which are more than made up for by tax revenue. Counterfactuals that solve for new taxes suggest that a much higher tax schedule is required to divert even modest market shares to low-congestion modes of transportation.

The results point to the nuance required in policies designed to alleviate congestion. For example, Barwick et al. (2023) find that a combination of congestion pricing and subway expansion yields the largest reduction in congestion and efficiency gains. Although I am precluded from detailed counterfactuals such as these due to data limitations, it is a promising area for future research.

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References

Almagro, M., Castillo, J.C., Hickok, N., de Matos, F.K.B., Salz, T., 2023. Public Transit Potential. Working Paper .

Anas, A., Lindsey, R., 2011. Reducing Urban Road Transportation Externalities: Road Pricing in Theory and in Practice. Review of Environmental Economics and Policy .

Anderson, M., 2014. Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion. American Economic Review 104, 2763 – 2796.

Anderson, M., Davis, L., 2023. Uber and Traffic Fatalities. Review of Economics and Statistics Forthcoming.

Barwick, P.J., Li, S., Waxman, A., Wu, J., Xia, T., 2023. Efficiency and Equity Impacts of Urban Transportation Policies with Equilibrium Sorting. Working Paper .

Basso, L., Silva, H., 2014. Efficiency and Substitutability of Transit Subsidies and Other Urban Transport Policies. American Economic Journal: Economic Policy 6, 1 – 33.

Bento, A., Cropper, M., Mobarak, A.M., Vinha, K., 2005. The Effects of Urban Spatial Structure on Travel Demand in the United States. The Review of Economics and Statistics 87, 466 – 478.

Bento, A., Goulder, L., Jacobsen, M., Haefen, R., 2009. Distributional and Efficiency Impacts of Increased US Gasoline Taxes. American Economic Review 99, 667 – 699.

Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile Prices in Market Equilibrium. Econometrica 63, 841 – 890.

Besley, T., Rosen, H., 1999. Sales Taxes and Prices: An Empirical Analysis. National Tax Journal 52, 157 – 178.

Buchholz, N., 2022. Spatial Equilibrium, Search Frictions, and Dynamic Efficiency in the Taxi Industry. The Review of Economic Studies 89, 556 – 591.

Castillo, J.C., 2022. Who Benefits from Surge Pricing? Working Paper .

Cohen, P., Hahn, R., Hall, J., Levitt, S., Metcalfe, R., 2016. Using Big Data to Estimate Consumer Surplus: The Case of Uber. NBER Working Paper .

Davis, L., 2008. The Effect of Driving Restrictions on Air Quality in Mexico City. Journal of Political Economy 116, 38 – 81.

Davis, L., Sallee, J., 2020. Should Electric Vehicle Drivers Pay a Mileage Tax? . Environmental and Energy Policy and the Economy 1.

Doyle, J., Samphantharak, K., 2008. $2.00 Gas! Studying the Effects of a Gas Tax Moratorium. Journal of Public Economics 92, 869 – 884.

Duranton, G., Turner, M., 2011. The Fundamental Law of Road Congestion: Evidence from US Cities. American Economic Review 101, 2616 – 2652.

Farronato, C., Fradkin, A., 2022. The Welfare Effects of Peer Entry: The Case of Airbnb and the Accommodation Industry. American Economic Review 112, 1782 – 1817.

Fréchette, G.R., Lizzeri, A., Salz, T., 2019. Frictions in a Competitive, Regulated Market: Evidence from Taxis. American Economic Review 109, 2954 – 2992.

Gaineddenova, R., 2022. Pricing and Efficiency in a Decentralized Ride-Hailing Platform. Working Paper .

Gu, Y., Chang, J., Zhang, J., Zou, B., 2021. Subways and Road Congestion. American Economic Journal: Economic Policy 13, 83 – 115.

Hall, J., 2018. Pareto Improvements from Lexus Lanes: The Effects of Pricing a Portion of the Lanes on Congested Highways. Journal of Public Economics 158, 113 – 125.

Jerch, R., Barwick, P.J., Li, S., Wu, J., 2021. Road Rationing Policies and Housing Markets. Working Paper .

Kang, Y., Gao, S., Liang, Y., Li, M., Kruse, J., 2020. Multiscale dynamic human mobility flow dataset in the u.s. during the covid-19 epidemic. Scientific Data 7, 1 – 13.

Kenkel, D., 2005. Are Alcohol Tax Hikes Fully Passed Through to Prices? Evidence from Alaska. American Economic Review 95, 273 – 277.

Kreindler, G., 2018. The Welfare Effect of Road Congestion Pricing: Experimental Evidence and Equilibrium Implications. Working Paper .

Langer, A., Winston, C., 2008. Toward a Comprehensive Assessment of Road Pricing Accounting for Land Use. Brookings-Wharton Papers on Urban Affairs , 127 – 175.

Leccese, M., 2021. Asymmetric Taxation, Pass-through and Market Competition: Evidence from Taxis and Ride-sharing. Working Paper .

Leccese, M., 2024. Do Minorities Pay More for Congestion Taxes? Evidence from a Tax on Ride-sharing. Working Paper .

Li, S., Linn, J., Muehlegger, E., 2014. Gasoline Taxes and Consumer Behavior. American Economic Journal: Economic Policy 6, 302 – 342.

Li, Z., Liang, C., Hong, Y., Zhang, Z., 2022. How Do On-demand Ridesharing Services Affect Traffic Congestion? The Moderating Role of Urban Compactness. Production and Operations Management 31, 239 – 258.

Liang, Y., Yu, B., Zhang, X., Lu, Y., Yang, L., 2023. The short-term impact of congestion taxes on ridesourcing demand and traffic congestion: Evidence from Chicago. Transportation Research Part A: Policy and Practice 172.

Mattia, A., 2023. The Value of Time: Evidence from Traffic Congestion and Express Lanes. Working Paper .

Parry, I., Small, K., 2005. Does Britain or the United States Have the Right Gasoline Tax? American Economic Review 95, 1276 – 1289.

Parry, I., Small, K., 2009. Should Urban Transit Subsidies Be Reduced? American Economic Review 99, 700 – 724.

Rosaia, N., 2023. Competing Platforms and Transport Equilibrium. Working Paper .

Shapiro, M., 2018. Density of Demand and the Benefit of Uber. Research Collection School Of Economics , 1 – 74.

Viard, B., Fu, S., 2015. The Effect of Beijing's Driving Restrictions on Pollution and Economic Activity. Journal of Public Economics 125, 98 – 115.

Weyl, G., Fabinger, M., 2013. Pass-Through as an Economic Tool: Principles of Incidence under Imperfect Competition. Journal of Political Economy 121, 528 – 583.

Yang, J., Chen, S., Qin, P., Lu, F., Liu, A.A., 2018. The Effect of Subway Expansions on Vehicle Congestion: Evidence from Beijing. Journal of Environmental Economics and Management 88, 114 – 133.

Yang, J., Purevjav, A.O., Li, S., 2020. The Marginal Cost of Traffic Congestion and Road Pricing: Evidence from a Natural Experiment in Beijing. American Economic Journal: Economic Policy 12, 418 – 453.

Zhang, W., Lawell, C., Umanskaya, V., 2017. The Effects of License Plate-Based Driving Restrictions on Air Quality: Theory and Empirical Evidence. Journal of Environmental Economics and Management 82, 181 – 220.

Zheng, Y., Meredith-Karam, P., Stewart, A., Kong, H., Zhao, J., 2023. Impacts of Congestion Pricing on Ride-hailing Ridership: Evidence from Chicago. Transportation Research Part A: Policy and Practice 170.

Appendix A. Passthrough Conditions

This section provides brief derivations of the main results in the text. Under the assumptions that prices only depend on respective taxes, prices are linear in taxes, taxes only affect mean utilities through price changes, and a logit demand system, the derivative of the market share of good j with respect to a tax on good k is given by:

$$\frac{\partial s_j}{\partial \tau_k}\Delta\tau_k = \begin{cases} \frac{\alpha \frac{\partial p_j}{\partial \tau_j}\Delta\tau_j V_j\left(1+\sum_{\ell\neq j} V_\ell\right)}{\left(1+\sum_{\ell\neq j} V_\ell\right)^2} & k=j \\ -\frac{\alpha \frac{\partial p_k}{\partial \tau_k}\Delta\tau_k V_k V_j}{\left(1+\sum_{\ell\neq j} V_\ell\right)^2} & k\neq j \end{cases} = \begin{cases} \alpha \frac{\partial p_j}{\partial \tau_j}\Delta\tau_j s_j(1-s_j) & k=j \\ -\alpha\frac{\partial p_k}{\partial \tau_k}\Delta\tau_k s_j s_k & k\neq j \end{cases} \tag{A1}$$

I also assume that $\frac{\partial p_j}{\partial \tau_k}=0$ for all $j\neq k$. As in Leccese (2024), this allows counterfactual analyses utilizing reduced form estimates of passthrough. The derivative of the market share of good j with respect to the entire tax schedule amounts to summing derivatives scaled by their discrete changes in taxes, as computed above. Summing yields the following:

$$\frac{\partial s_j}{\partial \tau} = \alpha\frac{\partial p_j}{\partial \tau_j}\Delta\tau_j s_j(1-s_j) - \sum_{k\neq j}\alpha\frac{\partial p_k}{\partial \tau_k}\Delta\tau_k s_j s_k = \alpha s_j\left[\frac{\partial p_j}{\partial \tau_j}\Delta\tau_j - \sum_k \frac{\partial p_k}{\partial \tau_k}\Delta\tau_k s_k\right]$$

I operate under the same set of assumptions with a nested logit framework:

$$\frac{\partial s_j}{\partial \tau_k}\Delta\tau_k = \begin{cases} \frac{\alpha}{1-\sigma}\frac{\partial p_j}{\partial \tau_j}\Delta\tau_j s_j\left[1-\sigma\bar{s}_{j|g}-(1-\sigma)s_j\right] & k=j \\ -\alpha\frac{\partial p_k}{\partial \tau_k}\Delta\tau_k s_k s_j\left(1+\frac{\sigma}{(1-\sigma)\bar{s}_g}\right) & k\neq j,\ \ k\in g(j) \\ -\alpha\frac{\partial p_k}{\partial \tau_k}\Delta\tau_k s_k s_j & k\neq j,\ \ k\notin g(j) \end{cases} \tag{A2}$$

The relevant moment for the change in market share for good j with respect to a change in the tax schedule is thus:

$$
\begin{aligned}
\frac{\partial s_j}{\partial \tau} &= \frac{\alpha}{1-\sigma}\frac{\partial p_j}{\partial \tau_j}\Delta\tau_j s_j\left[1-\sigma\bar{s}_{j|g}-(1-\sigma)s_j\right] + \sum_{k\neq j,\, k\in g(j)} \frac{\partial s_j}{\partial \tau_k}\Delta\tau_k + \sum_{k\notin g(j)} \frac{\partial s_j}{\partial \tau_k}\Delta\tau_k \\
&= \frac{\alpha}{1-\sigma}\frac{\partial p_j}{\partial \tau_j}\Delta\tau_j s_j - \sum_{k\in g(j)} \alpha\frac{\sigma}{(1-\sigma)\bar{s}_g}\frac{\partial p_k}{\partial \tau_k}\Delta\tau_k s_k s_j - \sum_k \alpha\frac{\partial p_k}{\partial \tau_k}\Delta\tau_k s_j s_k \\
&= \frac{\alpha}{1-\sigma}s_j\left[\frac{\partial p_j}{\partial \tau_j}\Delta\tau_j - \sigma\sum_{k\in g(j)}\frac{\partial p_k}{\partial \tau_k}\Delta\tau_k\bar{s}_{k|g} - (1-\sigma)\sum_k\frac{\partial p_k}{\partial \tau_k}\Delta\tau_k s_k\right]
\end{aligned}
$$

Appendix B. Methodology

Appendix B.1. Difference-in-Differences

A primary question is how the tax differentially affected high-tax areas relative to low-tax areas. The first econometric approach is a difference-in-differences:

$$\bar{y}_{it} = \alpha_i + \gamma_t + \theta D_{it} + \varepsilon_{it} \tag{B1}$$

Each variable is indexed by day t and location i. α is a set of location fixed effects and θ is a set of date fixed effects. D_{it} indicates whether or not an observation belongs to the treatment group (i.e. a high-tax area) and whether the new tax is in effect. θ captures the average treatment effect of the tax in high-tax areas relative to low-tax areas. The results are presented in Appendix C.

Appendix B.2. Regression Discontinuity

Difference-in-differences is not ideal because there is no true "control" group: every area experiences some form of an increase in taxes. Therefore, I also use a regression discontinuity design to estimate the effect of the new tax on ride-sharing services. As a baseline model, I evaluate a parametric regression discontinuity:

$$\bar{y}_{it} = \alpha_i + \tau_t + \theta D_{it} + \sum_{k=1}^{3}\beta_k(t-t^*)^k + \varepsilon_{it} \tag{B2}$$

Each variable is indexed by location i and day t. D_i is the treatment variable for post-tax and analysis is conducted separately for high-tax and low-tax areas. α_i is a set of location fixed effects and τ_t is a set of day fixed effects. Note that including fixed effects is unnecessary for identification in a regression discontinuity, but they may reduce sample variance. However, regression discontinuity suffers from the same concern that the coefficient may pick up month fixed effects. The results are presented in Appendix C.

Appendix B.3. Safegraph Weights

The figure below shows the distribution of trips taken in the pre-period and post-period. Given that the Safegraph data is recorded at a daily level, I construct hourly measures of population flows by scaling the population flows according to the density observed in the ride-sharing and taxi data.

Appendix B.4. Consumer Sorting

A threat to identification comes in the form of consumer sorting. Consumers may switch to slightly earlier times to avoid the tax. In this case, the coefficients in the reduced form analysis would be biased. In order to assess the severity of potential sorting, I examine the density of ride-sharing by the number of minutes to the tax change in the pre-period and post-period. The number of minutes to the tax change is defined as the number of 15-minute intervals around 6:00 am or 10:00 pm. If sorting occurred, the post-period density should shift to times when the tax is not in effect.

Figure B2 shows the pre-period and post-period densities for the early and late cutoffs during the day. Neither density plot reveals any sorting behavior. This helps justify the identification of the difference-in-differences design.

Appendix B.5. Income Effects

I explore heterogeneity in the labor supply response with a triple differences specification that relies on quantiles of income in a driver's home location:

$$\begin{aligned}\log(n_{it}) = {} & \gamma_M + \beta_1 \text{Treatment}_{it} + \beta_2 \text{Post}_{it} + \beta_3 \text{Above Q(Income)} \\ & + \eta_1 \text{Treatment}_{it} \times \text{Post}_{it} + \eta_2 \text{Treatment}_{it} \times \text{Above Q(Income)} \\ & + \eta_3 \text{Post}_{it} \times \text{Above Q(Income)}[+\Lambda \text{MultiHomes}_{it}] \\ & + \theta \text{Treatment}_{it} \times \text{Post}_{it} \times \text{Above Q(Income)} + \varepsilon_{it}\end{aligned}$$

The regression is indexed by Zip home location i and starting month t. As before, γ_M are starting month fixed effects, Treatment denotes the treatment

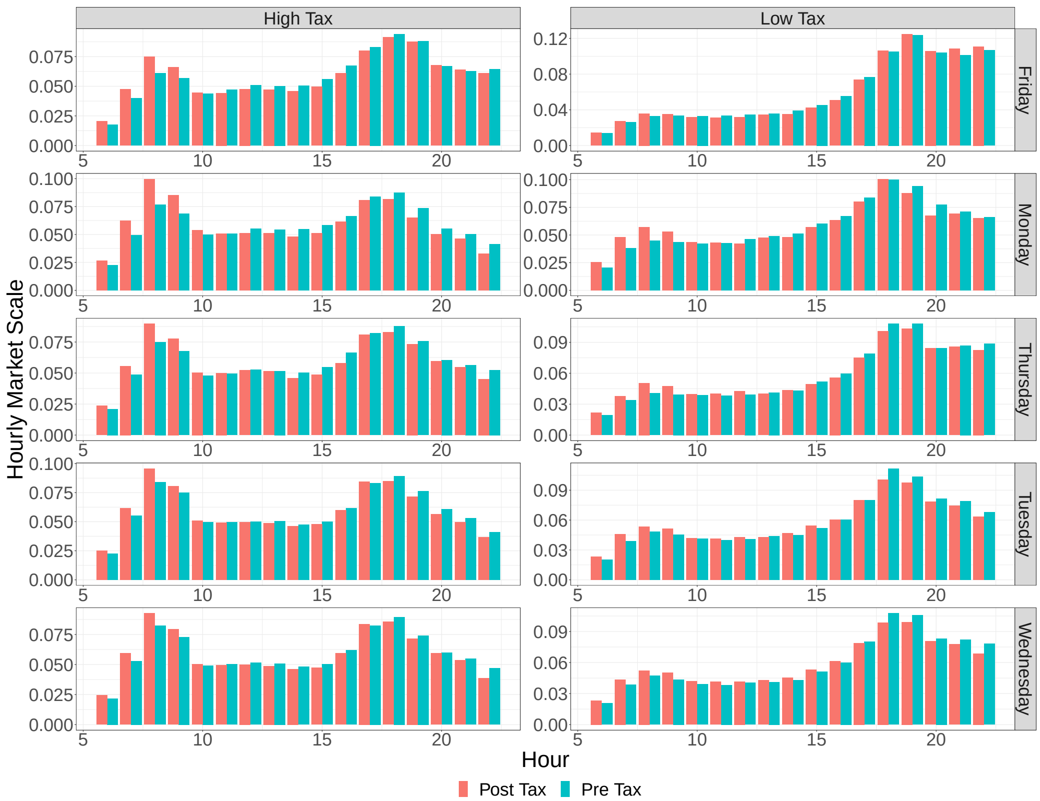

Figure B1: Market Size Scales

Notes: The figure presents the scales that are used to construct market sizes. The SafeGraph data is collected on a daily basis while the demand system is estimated at an hourly level. Assuming population flows follow the same hourly distribution as trips conditional on the day of the week, the daily population is scaled according to this distribution.

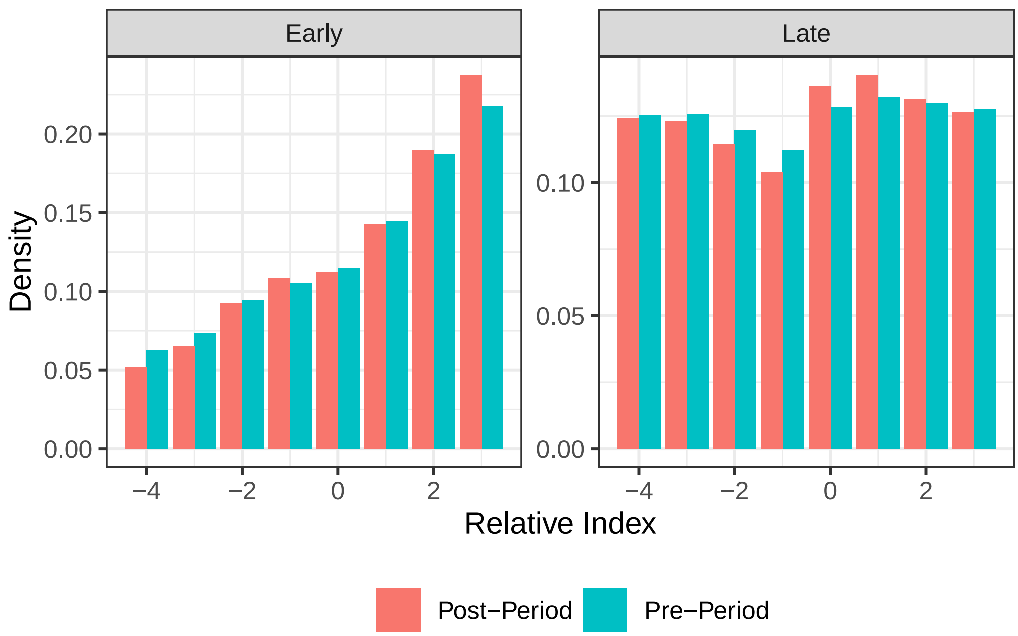

Figure B2: Temporal Sorting

Notes: The figure presents graphical evidence that there is no temporal consumer sorting to avoid the tax. Namely, the distribution of trips taken around the timing cutoff (6:00 am for Early and 10:00 pm for Late at Relative Index 0) does not appear to change comparing the pre-period to the post-period.

Table B1: Triple Differences Results

	Q = 0.5	Q = 0.75	Q = 0.85
Treatment × Post	-0.065***	-0.057***	-0.055***
	(0.018)	(0.013)	(0.012)
Treatment × Post × Above Q	0.034	0.033*	0.040*
	(0.021)	(0.020)	(0.021)

Notes: The table presents results from the triple differences specification for multi-homing drivers. $Q = 0.5$ refers to using the median as a cutoff for high income. Likewise, $Q = 0.75$ and $Q = 0.85$ refer to using the 75th and 85th percentiles as cutoffs for high income, respectively. The reported coefficients are from the interaction of treatment, post, and high income. *p<0.1; **p<0.05; ***p<0.01

group, Post indicates the post period, and MultiHomes indicates whether or not the driver multihomes. The variable Above Q(Income) is an indicator for whether a driver bin i comes from a Zip with median income above the given quantile Q(Income).

One explanation for the result that labor supply decreases for multi-homing drivers but not single-homing drivers is an income effect. Drivers who multihome are more likely to rely on driving as a primary source of income. As utilization decreased with the tax hike, the outside option — employment other than driving for platforms — became more attractive and these drivers chose to exit the market. Drivers who only drive for a single platform are less likely to use driving as a primary source of income, meaning this effect is less salient.

The regression analysis in Table B1 presents results from the triple differences specification for multi-homing drivers. The table reports the coefficients from the interaction of all indicators (treatment, post, and above a given quantile of income) and the interaction of the treatment and post indicators from the triple differences specification using different quantiles. The coefficients in the second and third columns suggest that there is some income effect using a quantile of home Zip as a proxy for driver income. The decrease in labor supply is mostly driven by multi-homing drivers, especially by those in lower-income home locations. This provides evidence of the income effect.

Appendix B.6. Discussion

Figure C7 presents the estimates of the change in consumer surplus by hour and day of the week. Unsurprisingly, evening commute times are affected the most by the tax, especially on Fridays. Morning commutes are affected the most during the middle of the week, and Friday nights are affected much more than other days of the week.

Appendix B.6.1. Increase Taxi Shares

The first counterfactual targets the share of taxis in an effort to reduce congestion by deterring ride-sharing trips. The model predicts a 1.4 percent increase in the conditional share of taxis after the implemented tax. I target a 3 percent increase in the share of taxis, double what the model predicts.

Figure C9 shows the change in tax schedule required to achieve a 3 percent increase in the share of taxis. Intuitively, across the board, taxis are subsidized while ride-share trips are taxed, especially solo trips in high-tax areas.

The results show that, to induce such a change in the share of taxis, taxis need to be subsidized on the order of 0.09-1.45 dollars in conjunction with heavy taxes on ride-share trips. The increases for solo trips are much higher than the realized tax changes at 0.53-4.59 dollars. The high end of the range naturally corresponds to the cases where taxis are not allowed to be subsidized. Increases for pooled trips are more modest and similar to the tax change in reality, ranging from -0.02-0.64 dollars. The high values are likely due to the nesting parameter that indicates most substitution occurs within platform products.

Appendix B.6.2. Increase Pooled Shares

The second counterfactual targets the share of pooled rides to reduce congestion by deterring solo ride-sharing trips, which likely induce more congestion than pooled trips. The model predicts a 2.5 percent increase in the share of pooled trips after the implemented tax. I target a 5 percent increase in the share of pooled trips, double what the model predicts.

Figure C10 shows the change in tax schedule required to achieve a 10 percent increase in the share of pooled trips. Intuitively, across the board, solo trips are taxed heavily, especially in high-tax areas, while pooled rides are subsidized and taxis are unaffected.

To induce this increase in the share of pooled trips, pooled rides need to be subsidized on the order of 0.22-0.93 dollars in low-tax areas and pooled rides in high-tax areas should not be taxed as high as the implemented policy. Meanwhile, solo trips need to be heavily taxed and taxis do not need to be taxed, which is intuitive given the strong correlation within platforms trips. The taxes on solo trips are more similar to the realized tax change than the previous counterfactual. The increase required for solo trips in low-tax areas is 0.82 dollars while the realized increase was 0.53 dollars; the increase required for solo trips in high-tax areas is 3.29 dollars while the realized increase was 2.28 dollars. In restricted scenarios, the tax change is at the upper end o f this range. The main change is the heftier subsidy for pooled rides in low-tax areas which is likely due to the larger passthrough of the subsidy. In the most constrained case, solo taxes nearly match the actual high-tax solo change and the pooled subsidies nearly match the actual low-tax pooled change.

Appendix B.6.3. Increase Diversion to the Outside Option

The third counterfactual targets the change in diversion to the outside option, i.e., the change in the inside share. Deterring all types of rides is a sure way to reduce congestion should the outside option include walking, biking, or public transportation. The model predicts an 8 percent decrease in the inside share after the implemented tax. I target a 20 percent decrease in the inside share, double what the model predicts.

Figure C11 shows the change in tax schedule required to achieve a 15 percent decrease in the inside share. Intuitively, across the board, all modes of transportation considered are taxed, especially solo trips.

To induce this decrease in the inside share, solo trips need to be taxed heavily, pooled trips need to be taxed moderately, and taxis need to be taxed lightly. Taxis require a light 0.06-0.93 dollar tax, depending on the area and scenario. Tax changes on solo trips range from 1.16-5.01 dollars. High-tax areas require a 4.68-5.01 dollar increase in taxes on solo trips, compared to the 2.28 dollar change that was implemented. Likewise, low-tax areas require a 1.16-1.25 dollar change, compared to the 0.53 dollar change in reality. The counterfactual taxes for pooled trips are closer to the implemented tax, ranging from 0.59-0.66 dollar increases. However, low-tax areas are quite different because they are not subsidized in any scenario, although they were in practice.

Appendix C. Tables and Figures

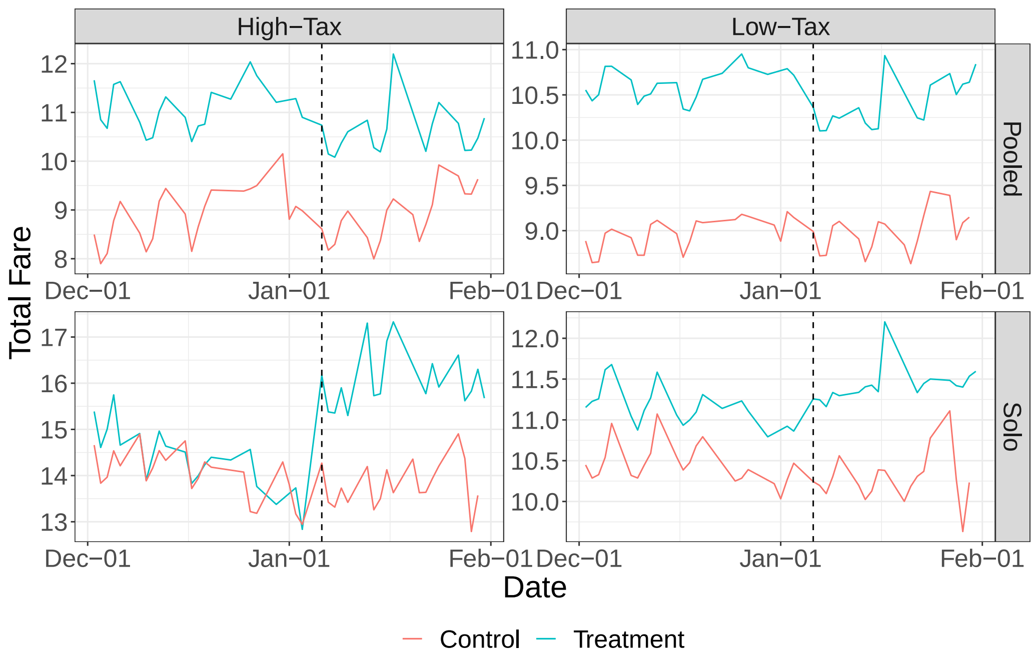

Figure C1: Discontinuity in Ride-Share Fares

Notes: The figure presents trends in total ride-sharing fares for solo and pooled trips on ride-sharing platforms. High Tax and Low Tax refer to areas with and without a surcharge, respectively. The control group (red) is the previous year of data and the treatment group (blue) is the more recent year that was affected by the tax change. Importantly, there were differential changes in total fares after the tax change, indicating imperfect passthrough.

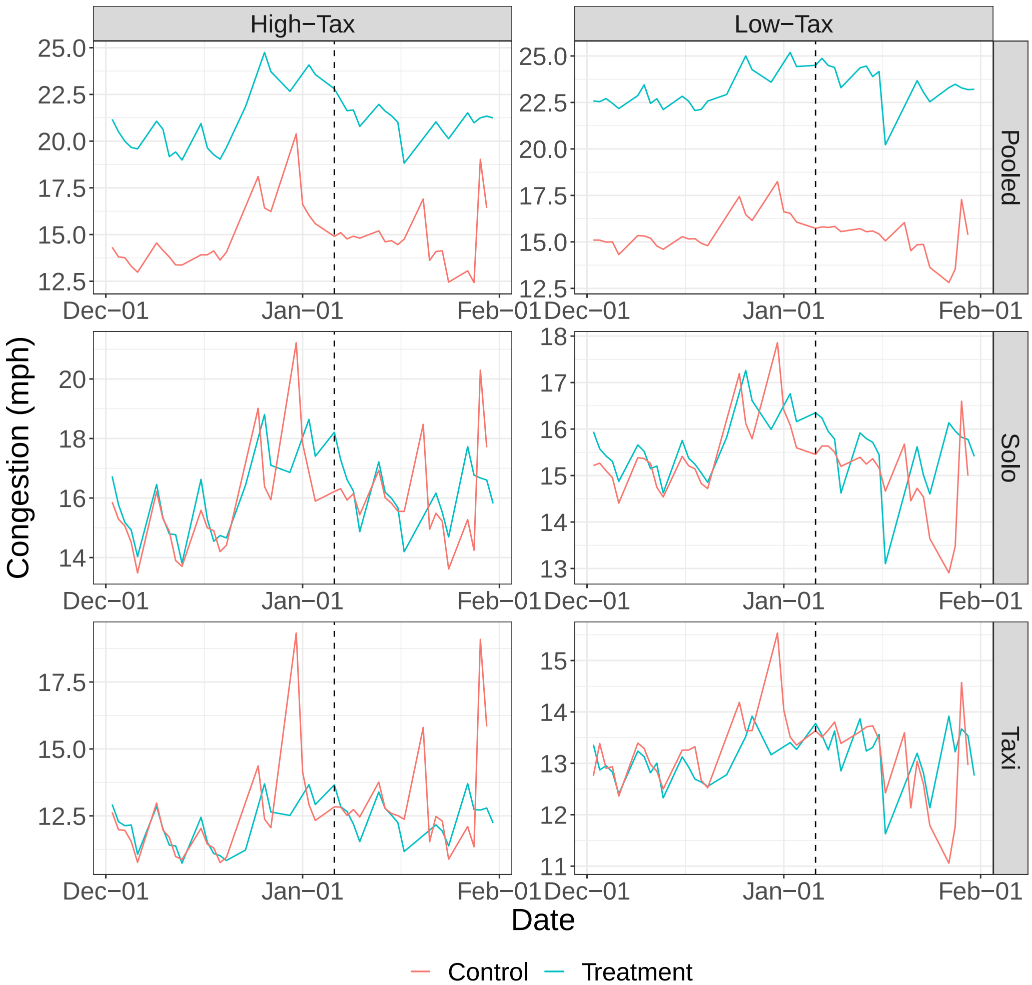

Figure C2: Congestion

Notes: The figure presents trends in trip speeds as a measure of congestion. Notably, a *higher* value indicates *lower* congestion. High Tax and Low Tax refer to areas with and without a surcharge, respectively. The control group (red) is the previous year of data and the treatment group (blue) is the more recent year that was affected by the tax change. There are no clear effects on congestion.

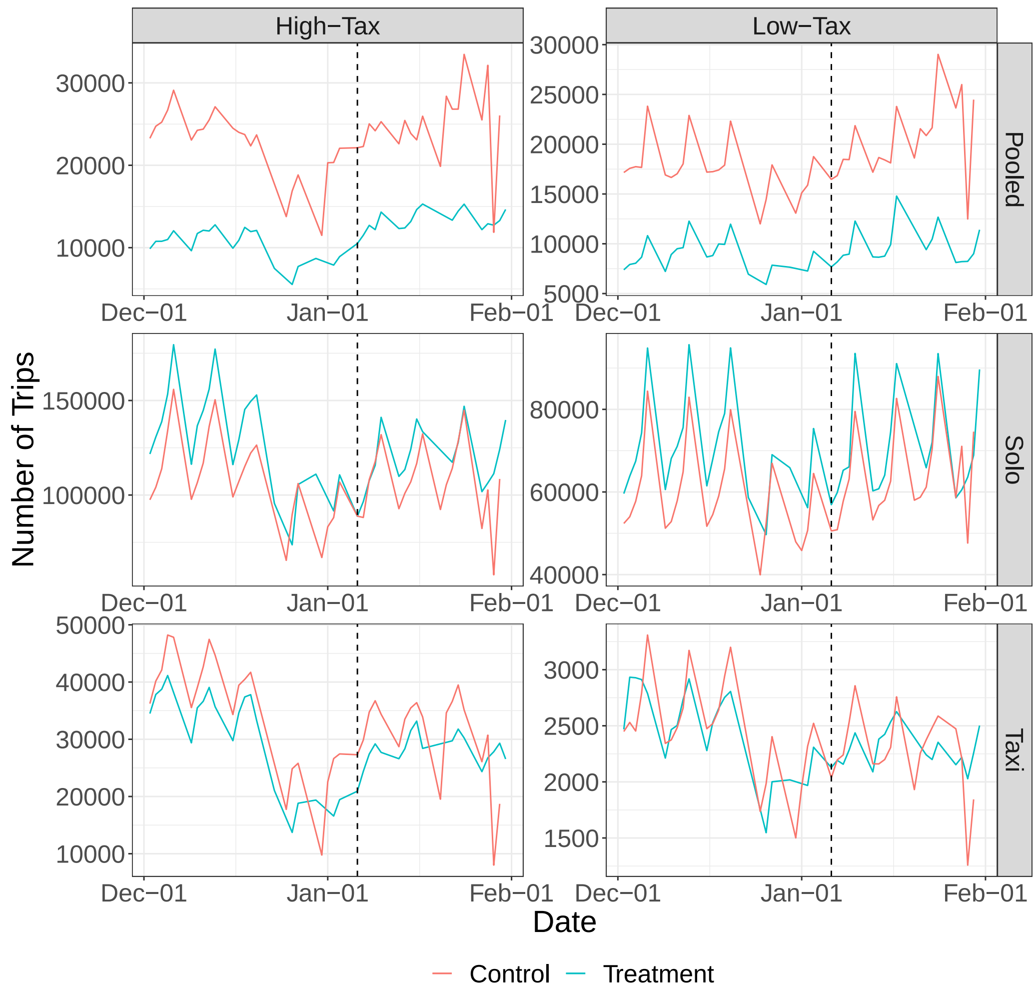

Figure C3: Ride-share Utilization

Notes: The figure presents trends in utilization across types of trips. High Tax and Low Tax refer to areas with and without a surcharge, respectively. The control group (red) is the previous year of data and the treatment group (blue) is the more recent year that was affected by the tax change. Utilization of solo trips appears to dip in the treatment year.

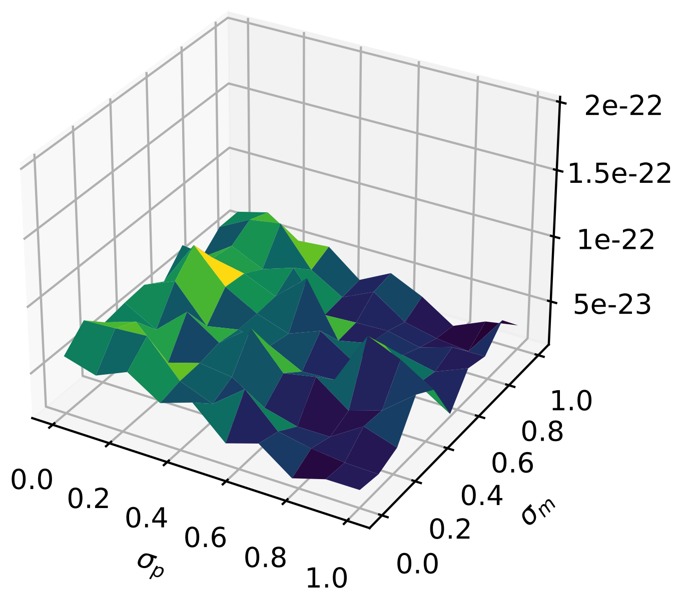

Figure C4: Objective Function over Σ

Notes: The figure presents the objective function of the demand specification with random coefficients on the constant and price. The data, including instruments, lack the variation required to identify random coefficients, as indicated by the flat objective function over values of Σ.

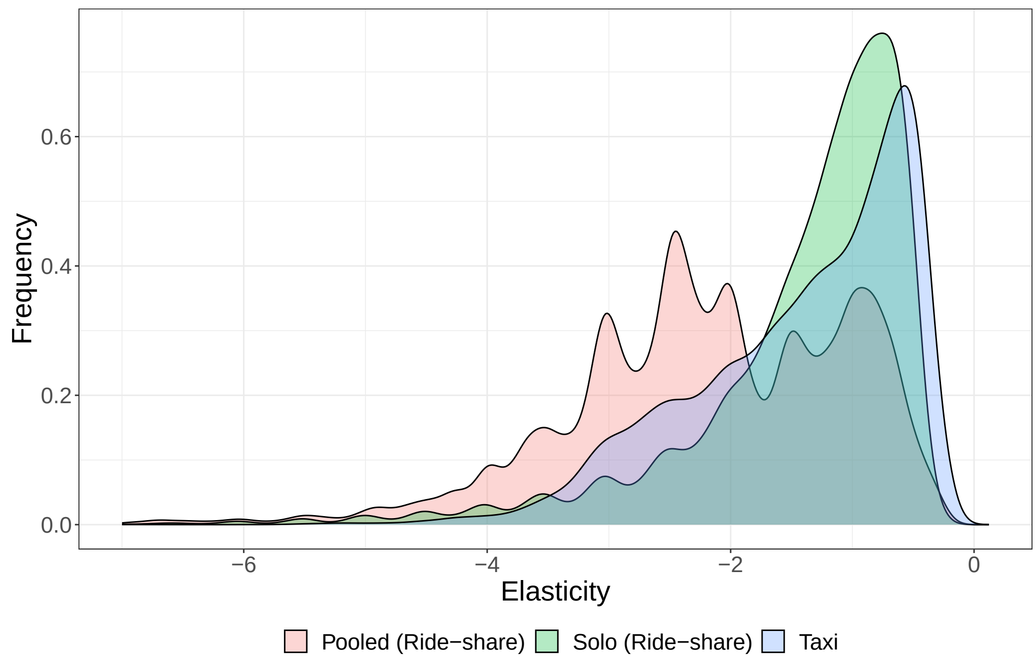

Figure C5: Mean Own-Price Elasticities

Notes: The figure presents the distribution of own-price elasticities by type of trip. Intuitively, individuals who take solo ride-share trips are much more inelastic than those who take pooled ride-share trips. Those who take taxi trips are more dispersed but are generally more elastic than those who take solo ride-share trips. The elasticities are based on column NL 2 in Table 6 with a nest for solo and pooled ride-sharing trips separate from taxi trips.

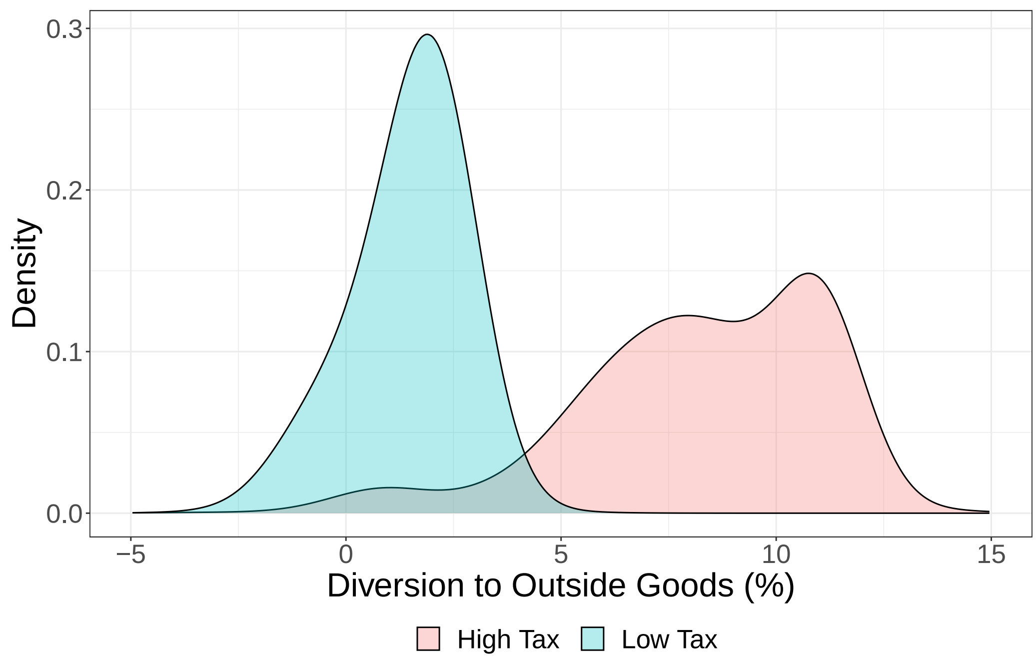

Figure C6: Diversion to Outside Goods

Notes: The figure presents the percentage change in the aggregate utilization of ride-sharing platforms and taxis as a result of the tax predicted by the model.

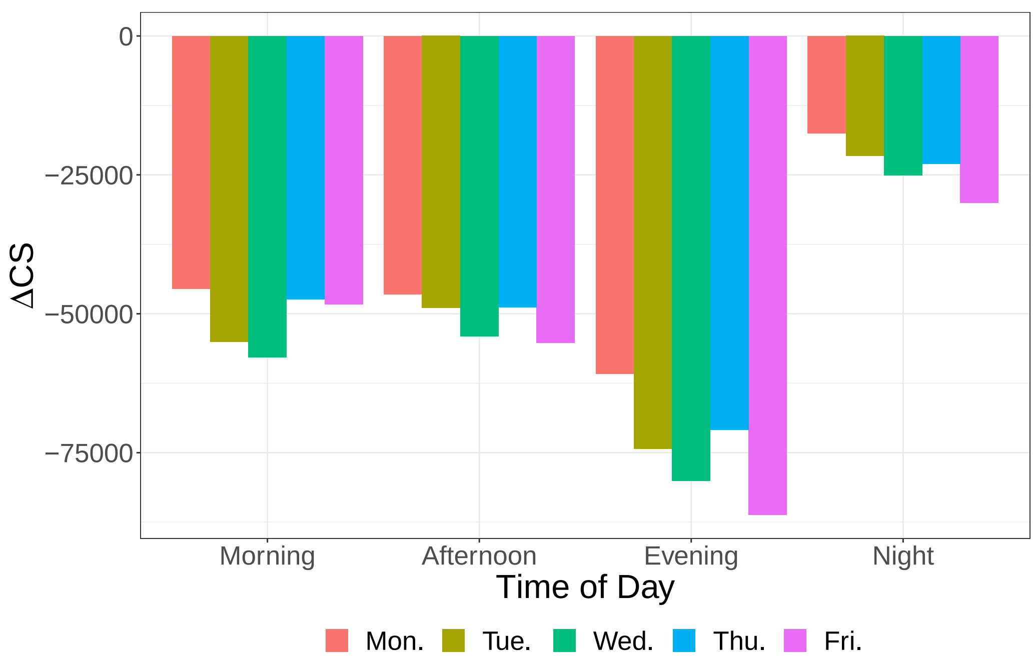

Figure C7: Change in Consumer Surplus

Notes: The figure presents the change in consumer surplus by the day of the week and hour as computed in the demand system. The selected markets are averages from before the tax change. Morning is before 10:00 am, Afternoon is before 3:00 pm, Evening is before 8:00 pm, and Night is after 8:00 pm.

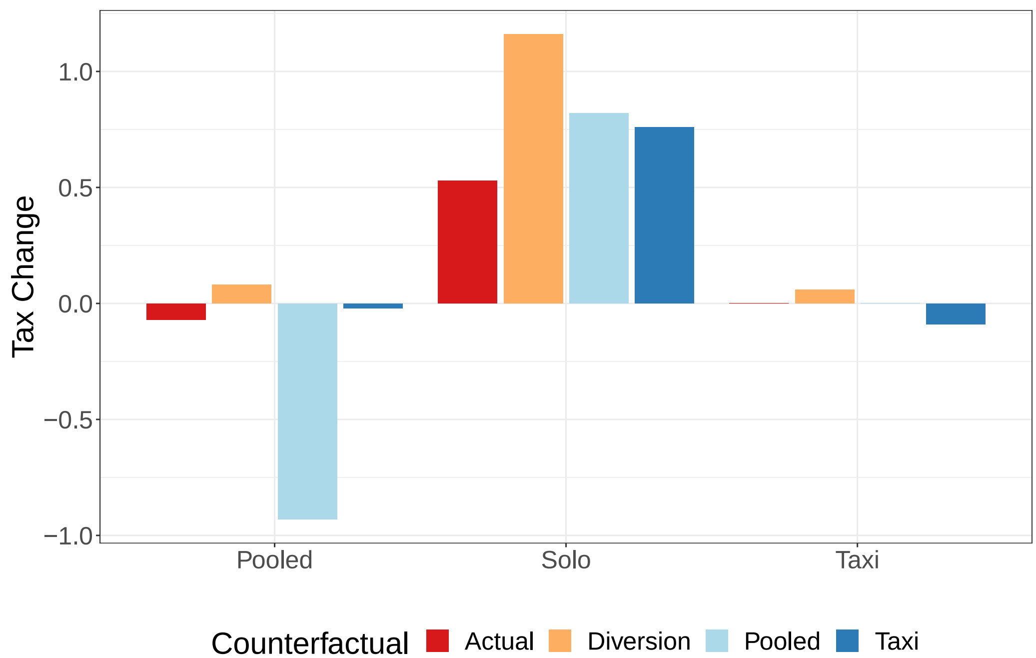

Figure C8: Counterfactuals

Notes: This figure represents potential changes in tax schedules (in dollars) that achieve different counterfactual goals: diversion to taxi trips, diversion to pooled trips, and diversion to the outside option. Each set of four bars is a mode (pooled, solo, and taxi). The four colors of bars represent different counterfactuals with the leftmost (red) being the implemented policy. The results presented are tax changes in low-tax areas.

	Actual Tax	Full	Single Tax	Platform Only	Single Tax, Platform Only
Taxi (L)		−0.09	−0.8		
Taxi (H)		−1.45	−0.8		
Solo (L)	0.53	0.76	2.88	1.11	3.86
Solo (H)	2.28	3.21	2.88	4.59	3.86
Pooled (L)	−0.07	−0.02	0.57	0.07	0.64
Pooled (H)	0.53	0.55	0.57	0.59	0.64

Figure C9: Taxi Target Counterfactual

Notes: This figure represents potential changes in tax schedules (in dollars) that achieve a one percent increase in the share of taxis and maintain an eight percent decrease in utilization. The first column represents the actual tax change and the remaining columns are counterfactuals. The second column allows fully flexible taxes across high-tax and low-tax areas with separate policies for taxis, solo ride-share, and pooled ride-share trips. The third column restricts policies to ride-sharing platforms. The last two columns are restricted to taxes on platforms only. The first allows taxes on solo and pooled trips to vary by location while the second does not. In summary, taxis are heavily subsidized (when possible) and platforms are heavily taxed, especially solo trips in high-tax areas.

	Actual Tax	Full	Single Tax	Platform Only	Single Tax, Platform Only
Taxi (L)		0	0		
Taxi (H)		0	0		
Solo (L)	0.53	0.82	3.07	0.82	3.07
Solo (H)	2.28	3.29	3.07	3.29	3.07
Pooled (L)	−0.07	−0.93	−0.22	−0.93	−0.22
Pooled (H)	0.53	0.16	−0.22	0.16	−0.22

Figure C10: Pooled Target Counterfactual

Notes: This figure represents potential changes in tax schedules (in dollars) that achieve a five percent increase in the share of pooled trips. The first column represents the actual tax change and the remaining columns are counterfactuals. The second column allows fully flexible taxes across high-tax and low-tax areas with separate policies for taxis, solo ride-share, and pooled ride-share trips. The third column restricts policies to ride-sharing platforms. The last two columns are restricted to taxes on platforms only. The first allows taxes on solo and pooled trips to vary by location while the second does not. In summary, solo trips are taxed heavily (especially in high-tax areas) and pooled rides are subsidized.

	Actual Tax	Full	Single Tax	Platform Only	Single Tax, Platform Only
Taxi (L)		0.06	0.57		
Taxi (H)		0.93	0.57		
Solo (L)	0.53	1.16	4.01	1.25	4.2
Solo (H)	2.28	4.68	4.01	5.01	4.2
Pooled (L)	−0.07	0.08	0.66	0.1	0.66
Pooled (H)	0.53	0.59	0.66	0.6	0.66

Figure C11: Diversion Target Counterfactual

Notes: This figure represents potential changes in tax schedules (in dollars) that achieve a 15 percent decrease in utilization. The first column represents the actual tax change and the remaining columns are counterfactuals. The second column allows fully flexible taxes across high-tax and low-tax areas with separate policies for taxis, solo ride-share, and pooled ride-share trips. The third column restricts policies to ride-sharing platforms. The last two columns are restricted to taxes on platforms only. The first allows taxes on solo and pooled trips to vary by location while the second does not. In summary, all areas and modes are taxed, especially solo ride-share trips in high-tax areas.

Table C1: Pooled Share Results

	Dependent variable:		
	Pooled Share		
	Aggregate	High Tax	Low Tax
Post	0.016***	0.015***	0.018***
	(0.001)	(0.001)	(0.003)
Treatment	-0.105***	-0.097***	-0.120***
	(0.004)	(0.006)	(0.003)
Treatment × Post	0.004***	0.011***	-0.007***
	(0.001)	(0.001)	(0.001)
Obs.	331K	57K	274K
Market FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Adj. R^2	0.713	0.840	0.603

Notes: The table presents results from the difference-in-differences specification for the share of pooled rides. Standard errors are clustered by market.

Table C2: Taxi Results

	Dependent variable:		
	Taxi Share		
	Aggregate	High Tax	Low Tax
Post	-0.020***	-0.029***	-0.001*
	(0.003)	(0.004)	(0.001)
Treatment	-0.018***	-0.024***	-0.006***
	(0.003)	(0.004)	(0.001)
Treatment × Post	0.014***	0.019***	0.004***
	(0.003)	(0.004)	(0.001)
Obs.	626K	137K	490K
Market FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Adj. R^2	0.146	0.114	0.026

Notes: The table presents results from the difference-in-differences specification for taxi outcomes. High Tax refers to areas with a downtown surcharge and Low Tax refers to areas without the surcharge. Standard errors are clustered by market.

Table C3: Congestion Results

	Dependent variable:		
	Log MPH		
	Aggregate	High Tax	Low Tax
Post	0.030***	0.033**	-0.022***
	(0.004)	(0.004)	(0.005)
Treatment	-0.019***	-0.016***	-0.074***
	(0.005)	(0.005)	(0.005)
Treatment × Post	0.005	0.004	0.024***
	(0.005)	(0.006)	(0.008)
Obs.	85K	35K	50K
Market FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Adj. R^2	0.868	0.936	0.275

Notes: The table presents results from the difference-in-differences specification for congestion as measured by the (log) speed of taxis. Standard errors are clustered by market.

Table C4: Heterogeneous Utilization Results with Previous Control

	Dependent variable:					
	Solo Trips		Pooled Trips		Taxi Trips	
	High Tax	Low Tax	High Tax	Low Tax	High Tax	Low Tax
Post	0.938	2.094***	4.053***	1.111***	-9.966**	-0.316***
	(1.762)	(0.354)	(0.566)	(0.074)	(3.200)	(0.090)
Treatment	32.114***	3.731***	-21.533***	-3.550***	-9.046**	-0.197
	(3.863)	(0.160)	(2.355)	(0.210)	(3.099)	(0.119)
Treatment × Post	-17.047***	-2.157***	1.014*	-0.691***	2.943*	0.011
	(3.836)	(0.295)	(0.401)	(0.053)	(1.181)	(0.071)
Pre-Period Mean	170.840	21.075	28.924	5.524	74.669	3.925
Obs.	56K	245K	46K	194K	35K	50K
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.940	0.916	0.816	0.737	0.910	0.887

Notes: The table presents results from the difference-in-differences specification for various utilization outcomes. High Tax refers to areas with a downtown surcharge and Low Tax refers to areas without the surcharge. Standard errors are clustered by market.

Table C5: Utilization Results

	Dependent variable:		
	Solo Trips	Pooled Trips	Taxi Trips
Post	1.831***	1.633***	-4.550**
	(0.442)	(0.120)	(1.416)
Treatment	9.027***	-7.128***	-4.136**
	(0.753)	(0.517)	(1.381)
Treatment × Post	-4.802***	-0.226*	1.457**
	(0.746)	(0.101)	(0.563)
Pre-Period Mean	48.788	10.033	33.059
Obs.	301K	240K	85K
Market FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Adj. R^2	0.939	0.811	0.908

Notes: The table presents results from the difference-in-differences specification for utilization including the previous year as a control. Standard errors are clustered by market.

Table C6: Passthrough Results

	Dependent variable: Base Fare			
	High Tax		Low Tax	
	Solo	Pooled	Solo	Pooled
Post	-2.223***	-0.367***	-0.474***	0.101***
	(0.013)	(0.012)	(0.005)	(0.008)
Treated	-0.009	824***	0.237***	0.550***
	(0.049)	(0.033)	(0.0015)	(0.014)
Treated × Post	1.663***	0.157***	0.332***	-0.137***
	(0.033)	(0.024)	(0.008)	(0.013)
Passthrough	0.729	0.296	0.626	1.957
Obs.	56K	46K	245K	194K
Market FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Adj. R^2	0.995	0.966	0.980	0.911

Notes: The table presents results from the difference-in-differences specification for passthrough. High Tax refers to areas with a downtown surcharge and Low Tax refers to areas without the surcharge. Standard errors are clustered by market.

Table C7: Changes in Labor Supply

	Control	Treated	Δ
Pre-period	108K	115K	-6,431
Post-period	107K	107K	-112
Δ	-791	-7,334	-6,543

Notes: The table presents a simple difference-in-differences for the number of ride-share drivers. The control group is the previous year of data, the pre-period refers to December, and the post-period refers to January.

Table C8: Difference-in-Differences Results

	Dependent variable:					
	Pooled Share		Log MPH		Log Trips	
Treatment	0.013	0.012	0.029	0.029	−0.023	−0.023
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Obs.	1.91M	1.91M	1.91M	1.91M	1.91M	1.91M
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	Yes	No	Yes	No	Yes
Adj. R^2	0.228	0.228	0.839	0.839	0.768	0.768

Notes: The table presents results from the difference-in-differences specification without the previous year as a control. Standard errors are clustered by market and $p < 0.01$ for all.

Table C9: Heterogeneous Difference-in-Differences Results

	Dependent variable:			
	Log MPH		Log Trips	
	Solo	Pooled	Solo	Pooled
Treatment	0.027***	0.027***	−0.038***	0.076***
	(0.001)	(0.004)	(0.002)	(0.003)
Obs.	1.68M	0.41M	1.68M	0.41M
Market FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Adj. R^2	0.888	0.199	0.767	0.493

Notes: The table presents results from the difference-in-differences specification without the previous year as a control. Standard errors are clustered by market.

Table C10: Main Regression Discontinuity Results

	Dependent variable:					
	Pooled Share		Log MPH		Log Trips	
	High Tax	Low Tax	High Tax	Low Tax	High Tax	Low Tax
Treatment	0.032	0.022	-0.111	-0.054	0.038	-0.094
	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)
Obs.	743K	1.1M	743K	1.1M	743K	1.1M
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.241	0.224	0.618	0.501	0.824	0.464

Notes: The table presents results from the regression discontinuity design without the previous year of data. High Tax refers to areas with a downtown surcharge and Low Tax refers to areas without the surcharge. Standard errors are clustered by market and $p < 0.01$ for all.

Table C11: Taxi Results

	Difference-in-Differences	*Regression Discontinuity*		
	Taxi Share	Aggregate	High Tax	Low Tax
Treatment	-0.000	0.030***	0.041***	0.001*
	(0.001)	(0.002)	(0.000)	(0.000)
Obs.	1.9M	1.9M	743K	1.1M
Market FE	Yes	Yes	Yes	Yes
Day FE	Yes	No	No	No
Adj. R^2	0.925	0.922	0.917	0.446

Notes: The table presents results from the difference-in-differences and regression discontinuity specifications for taxi outcomes without the previous year of data as a control. High Tax refers to areas with a downtown surcharge and Low Tax refers to areas without the surcharge. Standard errors are clustered by market.

Table C12: Passthrough Results

	Dependent variable: Base Fare			
	High Tax		Low Tax	
	Solo	Pooled	Solo	Pooled
Post	-0.559***	-0.210***	-0.152***	-0.036***
	(0.028)	(0.021)	(0.006)	(0.008)
Miles	0.990***	0.180***	0.747***	0.164***
	(0.127)	(0.012)	(0.025)	(0.004)
Seconds	0.005***	0.002***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Passthrough	0.755	0.603	0.713	1.517
Obs.	28K	21K	126K	87K
Market FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Adj. R^2	0.996	0.967	0.980	0.908

Notes: The table presents results from the passthrough specification without the previous year of data as a control. High Tax refers to areas with a downtown surcharge and Low Tax refers to areas without the surcharge. Standard errors are clustered by market.