The Effects of Targeted Platform Taxes: Evidence from the Ride-Sharing and Taxi Industry*

Mario Leccese†

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This paper examines the effects of taxes specifically targeting digital platforms by exploiting a large ride-sharing tax introduced in Chicago that applied to ride-sharing services but exempted traditional taxis. Introduced with the objective of reducing congestion, the policy imposed differentiated surcharges by trip type and location, with single rides starting or ending downtown facing fees of up to $3 per trip. Using high-frequency trip-level data and a difference-in-differences design, I show that the tax led to large and significant price increases across all types of ride-sharing trips, with pass-through rates exceeding 100%. The sharpest increases occurred for downtown trips, leading riders to substitute single with shared rides but leaving the number of taxi pickups unchanged. Outside downtown, higher ride-sharing prices reduced both single and shared trips, again without increasing taxi usage. Overall, the policy reduced the total number of daily rides and stimulated the usage of shared rides, modestly alleviating congestion. However, the benefit was concentrated in the downtown area, and its magnitude remained modest for ride-sharing users relative to the tax amount.

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†Boston University, Questrom School of Business. Email: leccese@bu.edu.

1. Introduction

When deciding whether to tax a product, policymakers typically consider the effects of the intervention on price and output. For this reason, the study of tax pass-through has received considerable attention in economics (Kotlikoff and Summers 1987; Fullerton and Metcalf 2002). While most of this literature focuses on schemes imposing the same tax amount on all products in the industry, in practice, many taxes target only a subset of firms or products, and may even impose different amounts depending on the firm or product characteristics. These targeted taxes are often motivated by the goal of correcting negative externalities—such as pollution, congestion, or health harms—that vary across products. In other cases, they may also aim to offset regulatory asymmetries, particularly in settings where digital platforms compete with traditional firms subject to stricter regulatory regimes. For instance, platforms like Uber and Airbnb, which operate under more flexible regulatory frameworks than traditional taxis and hotels, compete directly with these incumbents and have been associated with externalities such as urban congestion and short-term housing shortages (Gurran and Phibbs 2017; Li et al. 2022).

While targeted taxation of platform services has gained traction in policy debates, its effects are not straightforward.[1] Depending on pass-through rates, platform-targeted taxes may impose substantial burdens on users, especially when price changes propagate across multiple sides of the platform. Moreover, by altering relative prices, these taxes may shift demand across services and reshape market competition. This paper empirically examines the pass-through and market effects of taxes targeting digital platforms that compete with traditional incumbents, and evaluates whether such policies effectively address the market failures they aim to correct.[2]

The tax implemented in Chicago since January 6, 2020 provides an informative case study to investigate these questions due to the large asymmetries in the tax amounts. Nominally motivated by a desire to reduce congestion and raise revenues for the city budget, the city of Chicago taxed ride-sharing (e.g., Uber and Lyft) but did not impose any surcharge to consumers taking rides with traditional taxis. In particular, Chicago replaced the flat fee of \$0.72 on all trips provided by a ride-sharing company with a tax

[1]Taxes specifically targeting some of the services offered by large digital platforms have been on the policy agenda since 2014. See for example, the OECD report available at: https://web-archive.oecd.org/2014-04-16/274984-comments-action-1-tax-challenges-digital-economy.pdf.

[2]A two-page summary of a previous version of this paper has been published as part of the Proceedings of the 23rd ACM Conference on Economics and Computation. See Leccese (2022) for additional details.

scheme that charges trips differently depending on the type of service (single or shared), its endpoints and time.[3] By taxing ride-sharing up to $3.00 per trip, this policy imposed the highest surcharge faced by ride-sharing companies in the US. In the month before the policy, taxis' average price per mile for a ride between two and four miles starting or ending in downtown Chicago was $4.94, whereas the same trip cost on average $4.30 per mile using the single service of ride-sharing companies. A ride of this kind faced the highest tax level under the new policy, and, if completely passed on to riders, the tax would make taxis cheaper.

The empirical approach of the paper leverages the introduction of the tax on ride-sharing trips as a source of exogenous variation to estimate the effects on prices, determine the tax pass-through rate, and quantify changes in the number of ride-sharing and taxi trips, as well as congestion measures. However, a simplistic comparison of market outcomes before and after the tax implementation would yield biased estimates, as the tax was introduced immediately following a period of holidays, during which activities typically slow down before picking up pace afterward. To address this issue of recurrent seasonal effects around the tax implementation date, I utilize a difference-in-differences design. This involves comparing the change in market outcomes after the tax was implemented on Monday, January 6, 2020, with the corresponding period in the preceding year.

This paper considers three questions in the context of the Chicago ride-sharing tax. First, I examine the pass-through of a transaction tax on ride-sharing services. These companies operate as peer-to-peer marketplaces (or, two-sided platforms) that connect riders with drivers. Pass-through may differ in this setting because platforms do not only account for riders' responses to the change in prices, but also internalize the potential change in drivers' willingness to supply rides. This can lead to even higher price increases. Second, I quantify the extent to which the tax shifts demand back to traditional taxis, and how this effect varies across different areas of the city. This sheds light on the substitutability between traditional taxis and ride-sharing and its determinants. Third, I consider the effect of the tax on congestion. The exacerbation of congestion is a critical issue in many large and growing metropolitan areas, and taxes have been a widely used tool to reduce traffic. Typically, these congestion charges have targeted all private vehicles (as seen in London) or, at the very least, both ride-sharing companies and traditional taxi services (as witnessed in New York City in 2019). However,

[3] I define shared rides as those in which riders make different bookings and are picked up separately. Prices for these rides refer to the price paid by each rider.

motivated by an internal analysis indicating that in Chicago ride-sharing companies are major contributors to traffic congestion, especially in the downtown area, the city justified the implementation of the tax as a targeted measure to tackle congestion.[4]

The results of my analyses provide evidence that taxing ride-sharing had economically significant effects on market outcomes. In particular, prices rose across all ride-sharing services, with tax pass-through rates exceeding 100%. Price increases were especially pronounced (more than 12%) for rides beginning or ending in the downtown area, where the tax was highest, prompting riders to substitute single with shared rides but leaving the number of taxi pickups unchanged. For rides starting and ending outside of downtown, the higher ride-sharing prices led to a decline in the usage of both types of ride-sharing services, again without affecting taxi pickups.

Overall, the tax hurt riders through higher ride-sharing prices and reshaped the demand for rides in Chicago, resulting in a decrease in the overall number of daily trips via ride-sharing and taxis. While this helped alleviate congestion, as evidenced by higher average speeds and reduced delay rates, particularly in downtown, the overall benefit remains relatively modest in terms of magnitude and economic significance. These findings suggest that road pricing targeting also taxis and private cars would be more effective in reducing traffic congestion.

Several empirical studies have documented a significant heterogeneity in the pass-through rates of taxes across different markets in which traditional one-sided firms operate (Poterba 1996; Besley and Rosen 1999; Kenkel 2005; Doyle and Samphantharak 2008).[5] However, the pass-through rates of taxes on ride-sharing platforms are affected by the fact they provide competing services—i.e., single and shared rides—(Besanko, Dubé and Gupta 2005; Agrawal and Hoyt 2019), and by network effects between drivers and riders.[6] Empirically studying the pass-through of taxes on two-sided platforms is particularly relevant in light of the recent initiatives undertaken by governments around the world aimed at capturing a larger part of the digital value creation through

[4]The internal study is available at: https://www.chicago.gov/content/dam/city/depts/bacp/Outreach%20and%20Education/MLL_10-18-19_PR-TNP_Congestion_Report.pdf, accessed on 2/26/2024.

[5]Specific attention has also been devoted to firms' and consumers' short-run responses to taxes. An example is offered by Hindriks and Serse (2019) who examine the short-run impact of a tax on alcoholic beverages on the retail prices of six major brands of spirits.

[6]A few existing papers have studied taxation in the context of two-sided markets. Bibler, Teltser and Tremblay (2021) show that the enforcement of a 10% tax reduces the price paid to Airbnb hosts by 2.4% and increases the total price renters pay by 7.6%. Wilking (2020) finds that shifting the obligation to remit taxes from independent renters to Airbnb increases both prices and revenues. In a different setting, Gorodnichenko and Talavera (2017) show how pass-through rates of exchange rate fluctuations are stronger (between 60% and 75%) in online markets than in regular stores.

taxes (Bourreau, Caillaud and De Nijs 2018).

This paper contributes to the empirical literature on the competition between online peer-to-peer platforms (Einav, Farronato and Levin 2016) and traditional incumbent firms. In industries such as taxis and hotels, the entry of platforms has significantly reduced incumbent revenues (Abraham et al. 2021; Zervas, Proserpio and Byers 2017). Similar effects can even be observed when entering platforms compete with incumbents only on one side of the market. For example, Craigslist's entry led to a reduction in circulation of newspapers with greater reliance on classified-ad revenues (Seamans and Zhu 2014).

These patterns have fueled an active policy debate over whether and how to regulate online peer-to-peer platforms. Even if taxes levied exclusively on platforms are arguably among the main tools on the agenda, relatively few papers have studied their effects.[7] Moreover, due to the lack of data covering actual policy changes, these studies considered the effects of taxing platforms only in counterfactual analyses, which required them to impose strong assumptions. For example, Shapiro (2018) studies the equilibrium impact of introducing a tax on Uber drivers whenever they pick up a passenger in Manhattan but assumes a tax pass-through rate of one. In the hotel industry, Farronato and Fradkin (2022) simulate how the market would be affected if Airbnb hosts, who are assumed to take prices as given, faced the same tax rate as hotels.[8] In contrast, using data covering the implementation of a tax on ride-sharing, I show that the tax affected the price and number of ride-sharing trips, leading to pass-through rates above one.

The focus on taxis and ride-sharing is particularly relevant in light of the stringent regulations characterizing the industry and the magnitude of the consequences of ride-sharing emergence. In effect, taxi fares are regulated and taxi drivers need to purchase a license (also known as medallion) in order to operate. By contrast, ride-sharing prices are freely determined through algorithms and drivers can join the platform at negligible costs.[9] Thus, the entry of ride-sharing platforms generated large benefits for consumer surplus via improved matching technology (Fréchette, Lizzeri and Salz 2019; Buchholz 2021) and surge pricing (Cohen et al. 2016; Castillo 2020) but, in some cities, it also

[7] Agrawal and Zhao (2023) develop and calibrate a model to study the general equilibrium effects of taxing Uber, focusing on its relationship with public transit usage. Via simulations, they show that taxes on Uber only mildly increase public transit usage but when Uber is subsidized as a last-mile provider, transit increases more.

[8] Li and Srinivasan (2019) instead simulate a policy raising Airbnb's operative cost by up to 130%, and find that hotel profits increase as Airbnb's host costs increase.

[9] The main costs of becoming an Uber or Lyft driver are hidden and include upgrading one's auto insurance and meeting vehicle requirements. According to the data published by the Business Affairs and Consumer Protection (BACP), in Chicago medallions were traded for prices as high as $390,000 in 2012.

coincided with the increase in congestion (Li et al. 2022) and the collapse of the value of medallions (Bagchi 2018).[10] In this context, taxing ride-sharing provides a tool to satisfy incumbents' demands for more protection and potentially reduce congestion. This paper shows how such interventions may have only a limited impact on incumbent revenues and modest benefits in reducing congestion, while significantly increasing prices for riders.[11]

The rest of the paper is organized as follows. Section 2 discusses the likely impacts of a tax on platforms' rides only. Section 3 describes the Chicago taxi and ride-sharing industry and the structure of the tax studied, whereas Section 4 describes the data. Section 5 presents the empirical strategy. The effects of the tax on prices, number of pickups and congestion are discussed in Section 6 and a conclusion is offered in Section 7.

2. Conceptual Framework

This section outlines the key economic mechanisms through which a tax on ride-sharing is likely to impact equilibrium prices and pickups in the taxi and ride-sharing industry, and discusses potential implications for congestion.

Standard tax incidence analysis suggests that pass-through rates depend on the relative elasticities of demand and supply. In competitive markets with constant marginal costs, taxes are typically fully passed through to consumers, while increasing marginal costs imply pass-through rates below one (Kotlikoff and Summers 1987; Fullerton and Metcalf 2002). In contrast, with imperfect competition, pass-through may be greater or less than one depending on the nature of competition and the shape of demand.[12] However, under common assumptions on demand and conduct—such as log-concave demand and Cournot competition between symmetric firms—overshifting is rare without extremely inelastic supply or demand (Weyl and Fabinger 2013).[13]

Since ride-sharing companies are peer-to-peer marketplaces, indirect network effects between drivers and riders may affect pass-through rates (Belleflamme and Toule-

[10] The crisis of the taxi industry in the US has received particular attention due to the financial difficulties of the drivers who had invested in the industry. See, for example, https://www.nytimes.com/2019/05/19/nyregion/taxi-medallions.html for an article about the NYC market.

[11] Additionally, taxes like the one implemented in Chicago can have substantial heterogeneous effects across different neighborhoods and times leading to potentially large distributional costs (Leccese 2024).

[12] See Katz and Rosen (1985); Stern (1987); Besley (1989); Delipalla and Keen (1992); Hamilton (1999); Anderson, Palma and Kreider (2001) for analytical models studying pass-through in oligopoly markets.

[13] Miklós-Thal and Shaffer (2021) refine the analysis in Weyl and Fabinger (2013), showing that their pass-through and incidence formulas are only valid for infinitesimal changes or linear demand.

monde 2018). In particular, since drivers adjust their labor supply in response to changes in earnings (Hall, Horton and Knoepfle 2021), the reduction in demand following a tax levied on riders reduces drivers' willingness to work for the platforms, and hence the aggregate supply of rides.[14] This, in turn, further increases the equilibrium price. Thus, in a two-sided market, the presence of indirect network effects inflates pass-through rates, making it easier to rationalize tax overshifting than it would be in a conventional one-sided firm analysis.

To formalize this intuition, suppose that ride-sharing companies only offer one type of service and consider a simple setting with $D(p)$ being a downward-sloping demand function at price p. The supply side is composed of a pool of N drivers, who at the beginning of each day decide whether to enter the market and work for the platform. I assume that drivers are heterogeneous with respect to their outside option ω ($\omega \sim U[0, \bar{\omega}]$), and decide whether to be on the market by comparing their outside option with the expected earnings from entering, $e = (1 - \nu) \cdot p \cdot \frac{Q}{L}$, where Q is the equilibrium number of rides, $L \leq N$ is the number of drivers who enter the market, and $\nu \in (0, 1)$ is the fee charged by the platform on each ride. Let $h_i(p)$ be the upward-sloping individual labor supply of driver i (in hours) once the entry decision has been taken. I assume that, conditional on entering, drivers are homogeneous in their individual labor supply (i.e., $h_i(p) = h(p) \ \forall i$), and that the platform converts labor into number of rides offered at a service rate $\sigma(L)$, with $\sigma'(\cdot) \geq 0$. Then, the aggregate supply of rides can be written as $S(p, L) = L \cdot \sigma(L) \cdot h(p)$.

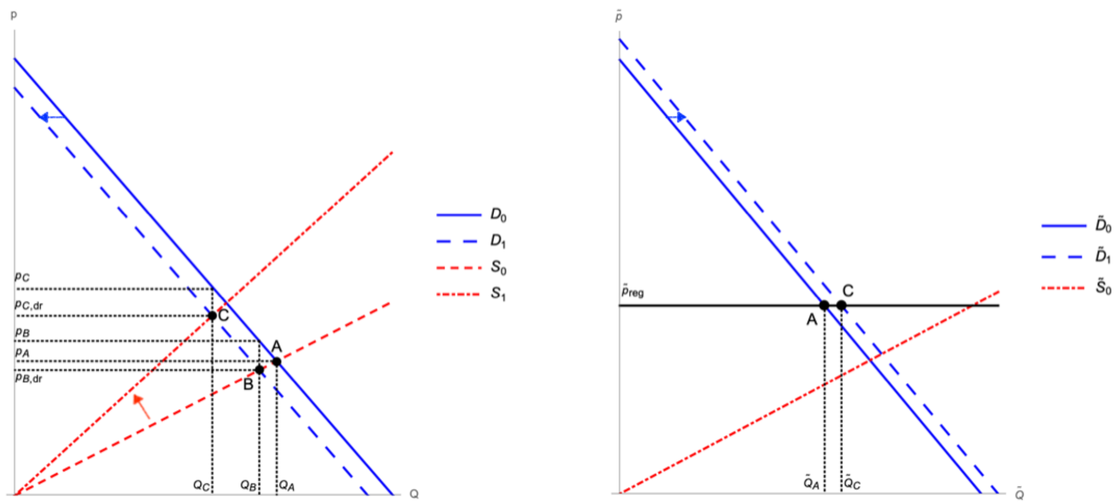
Figure 1A illustrates an example of the effect of a tax on ride-sharing in the setting above where only one type of ride-sharing trip is offered, assuming linear demand and supply.[15] The initial equilibrium is at point A. As the tax is levied on consumers, it prompts an inward parallel shift in total demand for ride-sharing. Thus, at B, the price paid by riders increases to p_B, while the price earned by drivers falls to $p_{B,\text{dr}}$. This would be the new equilibrium in a traditional one-sided analysis, with a pass-through rate lower than one. However, in the ride-sharing market, the decrease in the price drivers receive and in the number of rides reduces drivers' earnings, which in turn

[14] The link between the number of drivers and the aggregate supply of rides is also explored in Castillo, Knoepfle and Weyl (2022), who develop a model in which any change in the number of ride-sharing drivers in the market—which is a function of their expected earnings—shifts the aggregate supply of rides. However, their focus is on showing how ride-sharing markets are prone to a matching failure when demand is high relative to supply.

[15] Appendix A characterizes the post-tax equilibrium for the model with linear demand and supply, deriving necessary and sufficient conditions for a pass-through rate above 1. In addition, Table A.1 presents the values of model parameters and variables that would generate an effect similar to that in Figure 1A.

reduces L pivoting the supply curve. The final equilibrium in the example is at point C, where drivers receive a price higher than before the tax ($p_{C,\mathrm{dr}} > p_A$), and the pass-through rate is greater than one.

FIGURE 1. Effect of the tax on market equilibrium



A. Ride-sharing (Taxed) B. Taxis (Untaxed)

Notes: Figure A represents the impact of a tax on ride-sharing on demand and supply of ride-sharing assuming that only one service is offered by the platform. Figure B illustrates the potential effect of the same tax on the taxi market. Taxi prices do not change as they are regulated.

Another factor that may influence the impact of taxing ride-sharing platforms is that they generally offer two potentially competing services: single and shared rides. If the cross-price elasticity of substitution between these services is sufficiently high, substitution across products can amplify the effect of a tax levied on both services. A price increase in one service affects demand for the other, and if the platform internalizes this relationship in its pricing strategy, it may raise prices on both. In the presence of tax asymmetry within taxed services—as in my empirical context, where single rides face a higher surcharge than shared ones—demand will also shift toward the less heavily taxed option. Because shared rides generally account for a smaller share of the market, the net effect is likely to be a reduction in total ride-sharing demand and an increase in prices for both services.[16]

Since demand for ride-sharing and taxis may partially overlap, a larger increase in the price of ride-sharing can lead to a greater shift in demand toward traditional cabs.

[16]See Section A.1 in the appendix for a discussion of how competing services offered by platforms influence market outcomes.

Figure 1B illustrates the change in equilibrium in the taxi market, where $\tilde{D}(\tilde{p})$ and $\tilde{S}(\tilde{p})$ represent downward-sloping demand and upward-sloping supply, respectively. Fare regulation implies that taxi prices are fixed at $\tilde{p}$reg.[17] By raising ride-sharing prices, the tax shifts demand outward in the taxi market, increasing the equilibrium number of taxi rides from $\tilde{Q}_A$ to $\tilde{Q}_C$. The degree of substitutability between ride-sharing and taxis determines the size of this shift. If the cross-price elasticity of demand is sufficiently high, the tax will steer riders toward traditional cabs, reallocating both ridership and revenues away from ride-sharing platforms.

While the number of taxi and shared ride-sharing trips may increase in response to a tax that imposes a higher surcharge on single rides than on shared ones, and exempts taxis altogether, their smaller share relative to single ride-sharing trips suggests that the overall number of rides is likely to decline. This contraction in overall volume, combined with the fact that substitution from single to shared rides may reduce the number of vehicles on the road, could reduce congestion. However, the magnitude of this effect ultimately depends on the choices of riders who substitute away from ride-sharing: if a sufficient share shifts to non-car alternatives (e.g., public transit or walking), congestion may decrease; if instead a substantial share switches to private vehicles, the net effect could be limited or even adverse.[18]

In practice, additional factors beyond those discussed above, and not considered in my stylized framework, may shape the post-tax equilibrium. Differences in the shape of demand for single and shared rides can influence how prices and quantities adjust across services. For example, shared-ride users tend to be more price-sensitive, as they place a lower value on reduced waiting times (Alonso-González et al. 2021), potentially limiting price increases for that service. Spatial variation in demand density may also affect substitution patterns: in denser areas such as downtown, pooling is more feasible and taxis are more accessible, making substitution away from single ride-sharing more attractive (Shapiro 2018). Moreover, platforms may be able to strategically choose not only the price charged to riders, but also the effective wage paid to drivers.[19] Finally, tax overshifting may also reflect other strategic considerations. For example, by passing

[17] I assume that $\tilde{p}$reg is above the market-clearing price and that sufficient taxi licenses are available to accommodate the increase in demand. This assumption is supported by the decline in demand and revenues experienced by taxi owners in the U.S. after the entry of ride-sharing (Bagchi 2018).

[18] Almagro et al. (2024) show that road pricing can reduce congestion and environmental externalities but may also reduce traveler surplus if not accompanied by complementary transit investments.

[19] For example, this could happen by changing the commission fee, or through bonuses, promotions, and other incentives. Moreover, tipping can further complicate the mapping between rider payments and driver compensation.

through more than 100% of the tax, platforms can highlight to regulators that new surcharges directly burden riders, a signaling motive that goes beyond local profit maximization.[20]

In sum, targeted taxes on ride-sharing platforms can result in particularly large increases in prices, with pass-through rates potentially exceeding 100%. These policies may also reshape demand across services within the platform and reallocate market shares toward taxis. The magnitude of these effects, and whether such interventions meaningfully reduce congestion, is ultimately an empirical question, which I examine in the remainder of the paper.

3. Institutional Background

The taxicab industry is a critical component of the transportation infrastructure in large urban areas, generating about $31 billion in annual revenues in the US. Chicago is the third largest market in the US, after New York City and Los Angeles. In Chicago, the use of ride-sharing companies, also called Transportation Network Providers (TNPs), grew by 271% between 2015 and 2018—according to a report produced in 2019 by the Business Affairs and Consumer Protection of Chicago (henceforth, the 2019 BACP Report)—and this has substantially shrunk taxi drivers' earnings.[21]

Uber was the first TNP to enter the market, and in April 2013 allowed drivers to use their personal vehicles as part of UberX.[22] Lyft entered the Chicago market later in 2013. From that moment, the annual growth rate of taxi pickups experienced a slowdown, until it became negative in 2015. Between 2018 and 2020, Uber and Lyft offered two types of services: single rides and shared rides. Shared rides involved multiple passengers making separate bookings and being picked up along the same route. During this period, Via, a platform dedicated solely to shared rides, was also operating in Chicago alongside Uber and Lyft. Data by Second Measure, which tracks credit card expenditures, estimates that in November 2019 Uber commanded a roughly 72% market share in Chicago, while

[20]For instance, Uber and Lyft's decision to exit Austin in 2016 following the introduction of fingerprinting requirements illustrates that platform responses to regulation are shaped not only by short-run market incentives but also by broader strategic objectives. See the article available at: https://www.cnbc.com/2016/08/18/what-happened-in-austin-after-uber-and-lyft-got-up-and-left.html.

[21]The 2019 BACP Report "Transportation Network Providers and Congestion in the City of Chicago" is available at: https://www.chicago.gov/content/dam/city/depts/bacp/Outreach%20and%20Education/MLL_10-18-19_PR-TNP_Congestion_Report.pdf, accessed on 2/26/2024.

[22]Before April 2013 Uber offered only expensive cars (limos, UberBlack) and thus was not able to really compete with taxis.

Via had only a 1% market share.[23]

TABLE 1. Structure of the tax

Type of ride		Tax amount before January 6, 2020	Tax amount after January 6, 2020	Tax increment
Downtown:				
	Single TNP trip	$0.72	$3.00	+$2.28
	Shared TNP trip	$0.72	$1.25	+$0.53
	Taxi trip	$0.00	$0.00	$0.00
Non-downtown:				
	Single TNP trip	$0.72	$1.25	+$0.53
	Shared TNP trip	$0.72	$0.65	-$0.07
	Taxi trip	$0.00	$0.00	$0.00

Notes: The amounts refer to the tax paid by the provider to the City of Chicago for each trip completed. The table summarizes the amounts charged on different types of trips happening during peak times, defined as weekdays (Mondays, Tuesdays, Wednesdays, Thursdays, and Fridays) between 6 am and 10 pm.

Against this background, the City of Chicago in the 2019 BACP Report identified the entry of TNPs as the main reason for an increase in congestion. Therefore, with the explicit twofold purpose of reducing congestion and raising money to reduce the budget deficit, beginning on January 6, 2020, the city of Chicago implemented a new tax targeting trips completed by TNPs. Although one of the stated objectives was to reduce congestion, the tax did not affect traditional taxis or other private vehicles.

The structure of the tax is summarized in Table 1.[24] Before January 6, 2020, each trip supplied by a TNP was subject to a flat tax of $0.72, whereas no tax was imposed on taxi trips. The new tax schedule levied different amounts based on the type of ride (single or shared) and its geographical endpoints, distinguishing downtown rides from all the others. Downtown trips are those starting or ending (or both) within the area of Chicago downtown depicted in Figure 2. This definition implies that, for example, a trip starting in a peripheral neighborhood and ending in the downtown area would be defined as a downtown trip as much as a trip that happens entirely within the downtown zone.

[23] See https://www.reuters.com/article/uber-pricing-chicago-idUSL8N2816E8.

[24] Table 1 summarizes the tax applied to trips happening during weekdays between 6 am and 10 pm, which are the focus of my analyses. The tax also affected trips happening in other times or during weekends, as summarized in Table C.4 in the Appendix.

FIGURE 2. The Downtown zone

Source: City of Chicago. *Notes:* The figure depicts the downtown zone as defined by the City of Chicago in the new tax implemented starting on January 6, 2020.

As shown in Table 1, downtown rides experienced substantial tax increases: the tax on single rides rose to $3.00, marking a $2.28 increase from the previous flat fee of $0.72, while the tax on shared rides increased by $0.53 to $1.25. For non-downtown rides, the tax for single trips was raised to $1.25, whereas the tax on shared trips was reduced by $0.07, bringing it down to $0.65. This new tax schedule resulted in Chicago imposing the highest surcharge on TNPs in the United States. Notably, the policy did not impact taxi trips.

Many cities have used congestion pricing to tackle traffic. For example, in February 2019, to reduce congestion in Manhattan, NYC imposed a surcharge for trips that begin in, end in, or pass through Manhattan south of and excluding 96th Street (an area known as the congestion zone).[25] The surcharge was $2.75 for each single trip of TNPs, $0.75 per shared trip, and $2.50 per taxi trip. Although the NYC tax scheme varies between taxicabs and TNPs, this difference is very small in magnitude compared to that imposed by the Chicago tax, thus making the two interventions substantially different in their potential to affect competition in the market. Whether this additional effect was desired

[25] Other cities, such as London and Stockholm, have implemented congestion pricing policies, although these surcharges also affect private vehicles.

or not by the policymaker, the tax implemented in Chicago provides a unique quasi-experiment to study the effects of a targeted tax schedule on the competition between traditional taxis and ride-sharing.

4. Data

I use three different datasets. Below, I first describe each dataset and explain how I construct the sample. Then, I present descriptive analyses of the impact of the policy on TNPs' price-setting behavior.

4.1. Sources and Sample Construction

I combine data from two public sources: the City of Chicago Data Portal, which regularly provides detailed information on taxi and TNP trips, and the National Weather Service Forecast Office, which publishes data on the weather in Chicago over time. From the latter source, I use daily information on precipitation, wind speed, snowfall, and temperature.

The dataset for TNPs includes information on every trip since November 2018. Each observation includes the date, time, price, and endpoints of the ride, as well as other information including length (in miles), duration (in seconds), tolls, taxes, tip, and an identifier for whether the ride was shared (i.e., two or more riders booked separately and shared the ride).[26] However, the dataset does not specify the company that provided the ride and does not provide a driver identifier. Regarding the geographical endpoints of each ride, the data identifies the community area (CA) in which any trip started and ended. The city of Chicago is divided into 77 CAs. The areas' borders remained constant over the period I considered in the analyses, which allows me to compare results over time. The dataset on taxis includes information on every trip since 2013: miles, duration (in seconds), price, tip, driver identifier, pick-up and drop-off date, time, and location (expressed by the CA).

Given the structure of the tax, I focus on weekday trips starting after 6 am and ending before 10 pm.[27] This enables me to define four types of TNP rides: (i) downtown single rides, which are single TNP rides starting or ending within the downtown zone depicted

[26]For example, if passenger W is picked up in location A and dropped off in location B, and at some point during the trip passenger Z is picked up in location C and dropped off in location D, this would appear in the data as two separate observations with a shared ride flag on each record.

[27]I use weekdays' off-peak times only to construct a measure of congestion, as described in Section 6.3.

in Figure 2; (ii) downtown shared rides, which are shared TNP rides starting or ending within the downtown zone; (iii) other single rides, which are single TNP rides starting and ending outside the downtown zone; (iv) other shared rides, which are shared TNP rides starting and ending outside the downtown zone. Each of these types of rides faced the same flat tax of $0.72 before January 6, 2020, whereas afterward they started facing different surcharges. In particular, the tax on downtown single (shared) rides became $3 ($1.25), whereas that on all the other single (shared) rides became $1.25 ($0.65). Similarly, I distinguish downtown taxi rides from all other taxi rides. These rides were not affected by the tax.

To identify downtown trips, I leverage information provided in my data about the CA wherein each trip starts and ends. The downtown zone entirely includes the central business district of Chicago (the Loop) but also *partially* includes two CAs, i.e., the Near North Side and the Near West Side, which I refer to as "border areas." This implies that with my data, it is not possible to exactly identify the tax increment faced by trips originating or ending in a border area but with no endpoint inside the Loop. I refer to these rides as "border trips." Therefore, when studying the tax pass-through and its impact on taxi and ride-sharing pickups, I exclude border trips from my main analyses and conservatively identify the downtown zone with the Loop.[28] Nonetheless, due to the high volume of border trips, Appendix D provides a separate examination of the effects of the tax on the price and number of these specific rides. Additionally, I drop trips with a price above $200 and duration above two hours, which, however, only account for less than 0.01% of the rides.

For each type of ride, I construct a dataset where an observation is a route at a given hour (between 6 am and 10 pm) on a certain day, and a route is defined as the pair of CAs characterizing the origin and destination of a ride. Thus, an example of an observation in my dataset would be the price of a ride from Douglas—which is one of the 77 CAs of Chicago—to the Loop (downtown) between 3 and 4 pm on a given day. Furthermore, I consider two subsamples, which I refer to as "Sample 18-19" and "Sample 19-20," and I define two focal dates, one for each subsample. The focal dates are: (i) for Sample 19-20, Monday, January 6, 2020, which is when the tax began; and (ii) for Sample 18-19, Monday, January 7, 2019, which is the corresponding Monday in the year before the implementation of the tax. Each subsample is constituted by the nine weeks (Monday to Friday) before and the seven weeks after its respective focal

[28] When investigating the tax's impact on congestion, I will incorporate border trips into the primary analyses. This decision is motivated by the policy goal of reducing congestion in border areas.

TABLE 2. Summary statistics

	Sample 18-19, pre 01/07			Sample 18-19, post 01/07			Sample 19-20, pre 01/06			Sample 19-20, post 01/06		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	N	mean	sd	N	mean	sd	N	mean	sd	N	mean	sd
Panel A: Downtown Single TNP												
Number of pickups	19,107	42.46	124.4	42,713	38.01	112.3	20,566	47.86	140.2	45,314	39.95	115.6
Trip miles	19,107	8.761	4.099	42,713	8.772	4.130	20,566	9.017	4.134	45,314	8.967	4.113
Trip price ($)	19,107	19.46	6.946	42,713	19.11	6.806	20,566	19.25	6.570	45,314	20.61	6.415
Trip minutes	19,107	25.70	11.14	42,713	24.44	10.57	20,566	26.17	11.15	45,314	24.08	10.04
Trip speed (mph)	19,107	20.63	6.985	42,713	21.78	28.69	20,566	20.93	7.100	45,314	22.42	7.296
Panel B: Other Single TNP												
Number of pickups	219,551	4.678	13.91	504,653	4.825	14.31	268,422	5.095	14.74	588,536	5.020	14.98
Trip miles	219,551	6.616	5.382	504,653	6.658	5.412	268,422	7.046	5.586	588,536	7.037	5.580
Trip price ($)	219,551	16.17	9.002	504,653	16.10	8.801	268,422	16.48	8.545	588,536	16.87	8.525
Trip minutes	219,551	20.40	12.90	504,653	19.87	12.18	268,422	21.26	13.06	588,536	20.06	11.83
Trip speed (mph)	219,550	18.52	23.31	504,653	18.97	17.23	268,421	18.89	7.122	588,536	19.77	7.703
Panel C: Downtown Shared TNP												
Number of pickups	17,856	12.84	28.54	39,677	11.83	26.05	15,139	6.469	12.29	34,649	7.160	14.55
Trip miles	17,856	8.985	4.189	39,677	9.110	4.244	15,139	10.49	5.350	34,649	10.45	4.975
Trip price ($)	17,856	11.68	5.285	39,677	11.69	5.207	15,139	12.79	5.178	34,649	13.37	5.207
Trip minutes	17,856	31.12	12.88	39,677	29.91	12.33	15,139	30.19	13.25	34,649	27.81	11.95
Trip speed (mph)	17,856	17.41	5.727	39,677	18.32	5.920	15,139	21.60	9.613	34,649	23.35	9.692
Panel D: Other Shared TNP												
Number of pickups	207,529	2.865	4.806	475,146	2.887	4.771	164,442	1.996	2.232	381,986	2.063	2.363
Trip miles	207,529	6.571	4.970	475,146	6.863	5.157	164,442	7.766	6.212	381,986	7.704	5.921
Trip price ($)	207,529	10.91	5.958	475,146	11.02	5.905	164,442	11.88	5.783	381,986	11.96	5.926
Trip minutes	207,529	22.82	14.93	475,146	23.17	14.80	164,442	22.19	15.12	381,986	21.01	13.86
Trip speed (mph)	207,529	16.86	5.409	475,144	17.41	27.04	164,439	21.61	57.43	381,984	22.51	40.56
Panel E: Downtown Taxi												
Number of pickups	9,373	56.12	151.0	20,072	45.74	124.3	9,738	44.60	120.0	20,603	38.51	105.1
Trip miles	9,373	6.065	4.457	20,072	5.986	4.425	9,738	6.097	4.510	20,603	5.855	4.488
Trip price ($)	9,373	22.30	56.99	20,072	22.51	67.40	9,738	26.05	121.7	20,603	25.78	138.5
Trip minutes	9,373	21.36	12.00	20,072	20.48	11.42	9,738	22.47	12.21	20,603	20.83	11.42
Trip speed (mph)	9,351	16.53	8.469	20,031	17.80	116.5	9,733	16.28	30.73	20,593	16.77	55.29
Panel F: Other Taxi												
Number of pickups	39,175	2.751	4.592	85,501	2.467	3.547	42,525	2.501	4.047	91,126	2.223	3.158
Trip miles	39,175	5.526	6.166	85,501	5.383	6.167	42,525	5.550	6.242	91,126	5.250	6.110
Trip price ($)	39,175	20.96	49.12	85,501	20.99	68.66	42,525	22.23	72.16	91,126	21.62	83.50
Trip minutes	39,175	19.86	16.32	85,501	18.78	15.25	42,525	21.20	16.60	91,126	19.49	15.05
Trip speed (mph)	38,368	21.34	296.1	83,619	18.22	167.4	41,461	14.08	11.91	88,613	14.42	15.41

Notes: The table presents summary statistics for each route-hour-date in which at least a trip occurred in Sample 18-19 or Sample 19-20. Each panel refers to one of the six different types of rides considered.

date. This implies that observations between 11/5/2018 and 2/22/2019 belong to Sample 18-19, whereas observations between 11/4/2019 and 2/21/2020 belong to Sample 19-20.

As detailed in Section 5, my strategy for the identification of the effect of the tax on market outcomes will rely on comparing the change implied by the tax after January 6, 2020 in Sample 19-20 to that occurred in Sample 18-19 after January 7, 2019. To make the two subsamples comparable and aligned, I drop the week of Thanksgiving 2018 and that of Thanksgiving 2019 as well as the the one following Thanksgiving 2018 and that preceding Thanksgiving 2019 because Thanksgiving happened in different weeks of November in the two subsamples. Furthermore, I also exclude the weeks including Christmas 2018 and Christmas 2019 because they tend to be characterized by unusual riding patterns. In the Appendix, I discuss the robustness of my results to including also these weeks in my final sample. Therefore, eventually, I consider for each subsample six weeks before and seven weeks after its focal date. The choice regarding the number of weeks to include in a subsample is constrained by the fact that TNP data are only available starting in November 2018 and by the need to limit data contamination due to the COVID-19 crisis. Appendix B provides a detailed discussion and supporting evidence showing that excluding observations after February 21, 2020, helps mitigate concerns about sample contamination from COVID-19.

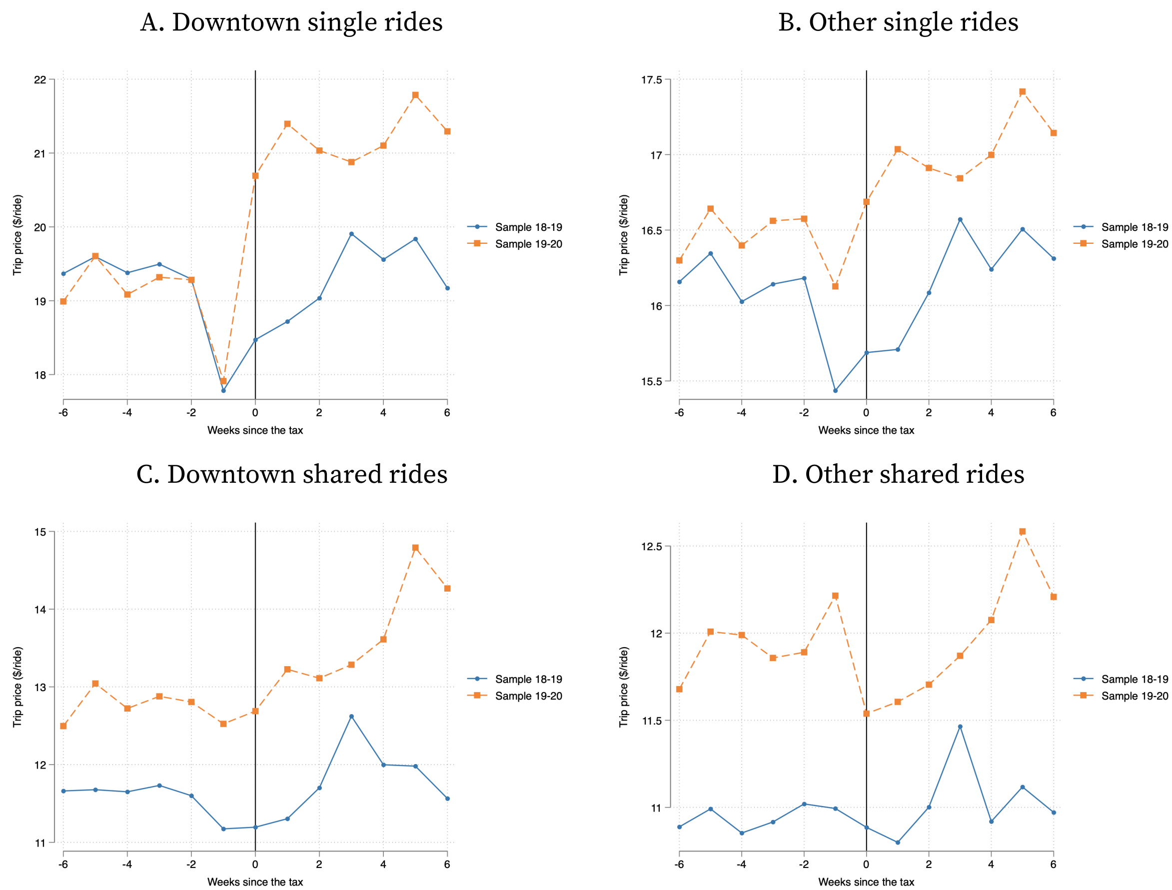
Table 2 displays summary statistics for my final sample. Each panel refers to a different type of ride and shows information about the key variables I consider in my analyses, splitting each subsample into the parts before and after its focal date. Specifically, every panel displays the average number of trips, the average price of a ride, the average length (in miles), the average duration (in minutes) and the average speed (in mph) per route-hour in which at least a trip occurred on a given day.

4.2. Descriptive Evidence

Providing suggestive evidence about the change in ride-sharing prices around the tax implementation date is a necessary first step in my analysis. Figure 3 illustrates how weekly average prices (in $ per ride) for different types of rides changed over weeks within Sample 18-19 and Sample 19-20. In all figures period 0 on the x-axis corresponds to the week starting on January 6, 2020 or January 7, 2019. All figures display substantial variation in price levels across weeks, but this variation is fairly similar across the two subsamples before period 0. This is also consistent with the absence of any response of TNP prices to the announcement of the tax on October 19, 2019.

Figure 3A shows that for single downtown rides, i.e. those for which the tax increment was the largest ($2.28), TNPs did not absorb the increase in the tax by reducing base fares (i.e., final prices net of taxes), implying a substantial lasting level increase in the final price paid by passengers. The comparison with the pattern of prices in the year before the tax implementation is consistent with the observed price changes not being entirely explained by seasonal effects. Figure 3B and 3C suggest a similar pattern for the price of non-downtown single and downtown shared rides, which both faced a

FIGURE 3. Change in TNP prices



Notes: Each figure plots weekly average prices (in $ per ride) for different types of rides changed against the weeks since period 0, which corresponds to the week starting on January 6, 2020 or January 7, 2019.

$0.53 tax increment in period 0.

Instead, for all the other shared rides, for which the tax fell by $0.07, Figure 3D displays a different pattern. In Sample 18-19, prices slightly decreased right after period 0 before increasing again in the following weeks. The drop in price in period 0 was substantially larger for Sample 19-20 relative to Sample 18-19. Nevertheless, afterward in Sample 19-20, prices steadily increased (until period 5) reaching levels higher than those prevailing before the tax was implemented. The magnitude of such an increase appears to be larger than the one displayed in Sample 18-19.

Lastly, except for downtown single rides, price levels are lower in Sample 18-19, even before period 0. This is consistent with the expansion and increase in prices over time of ride-sharing services, particularly shared ones.

5. Empirical Strategy

This section describes the main empirical design I adopt to identify the effect of the tax on prices, pickups and congestion.

My identification strategy exploits the exogenous variation provided by the implementation of the tax on January 6, 2020 to study the change in the outcomes of interest. However, a simplistic before and after comparison would lead to biased estimates of the impact of the tax because the policy started on the first Monday after a period of holidays, during which activities normally slow down.[29] To see this, consider for example Figure 3A. The average price of TNP single rides is subject to substantial seasonal variation, and prices tend to be lower at the end of the year (period -1 in the figure) to increase after period 0. This implies that, if I did not control for this seasonality, I could overestimate the causal impact of the tax on downtown TNP single rides. Moreover, a two-step procedure that first seasonally adjusts the data using several years of observations is not feasible in this setting as the City of Chicago started to collect data on TNP trips only in November 2018. Thus, to isolate the effect of the tax, I use a difference-in-differences (DiD) design and compare the change in the outcome variables after the tax implementation date (i.e., January 6, 2020) with the one that occurred after a hypothetical tax implementation date, which is defined as the first Monday after the same period of holidays in the previous year (i.e., January 7, 2019).[30] In other words, I pool together Sample 18-19 and Sample 19-20 and use the former as a control group.

The unit of analysis is a route i at hour h on date j in period t. For an observation belonging to Sample 19-20 (Sample 18-19), a period is defined as the number of days since January 6, 2020 (January 7, 2019). For example, $t = -1$ for January 3, 2020 and January 4, 2019—which are the weekdays immediately before January 6, 2020 and January 7, 2019, respectively—and $t = 1$ for January 7, 2020 and January 8, 2019. Note that by construction $t = 0$ for January 6, 2020 and January 7, 2019. In this way, for each period t, one can interpret observations belonging to Sample 19-20 as the treatment group, whereas those belonging to Sample 18-19 constitute the control group. Thus, I estimate several

[29] For example, using a local approach around the tax implementation date such as the Regression Discontinuity in Time design (e.g., Anderson (2014)), which is a regression discontinuity design that uses time as the running variable, would be subject to this concern.

[30] In their analysis of patients' response to dynamic incentives in health insurance contracts with deductible, Klein, Salm and Upadhyay (2022) build on a similar intuition to control for seasonality in healthcare needs.

equations of the following form:

$$y_{i,h,j,t} = \beta_0 + \beta_1 \cdot Sample1920_{i,h,j} + \beta_2 \cdot \left(Sample1920_{i,h,j} \times Post_t\right) + \\ + \beta_3 \cdot X_{i,h,j,t} + \alpha_i + \alpha_h + \alpha_t + \varepsilon_{i,h,j,t} \tag{1}$$

where $y_{i,h,j,t}$ is the outcome variable—e.g., the logarithm of the price of a ride—in route i at hour h of date j in period t; *Sample1920* is a dummy equal to one when the route-hour refers to a calendar date in Sample 19-20; *Post* equals one for observations in period 0 or later, i.e., $Post_t = 1\{t \geq 0\}$;[31] β_2 is the main coefficient of interest, capturing the effect of the tax on the outcome variable; X includes weather controls for each calendar date in Chicago, and, in some specifications, also controls for the average trip distance; α_i, α_h and α_t are route, hour and period fixed effects, respectively. These allow to control for any time-invariant route-, hour- or period-specific factors that might confound β_2. For example, any other (time-invariant) distance-related determinant of y not captured by the linear control for distance included in X is absorbed by α_i. Moreover, standard errors are two-way clustered by date and route to account for within-day shocks and serial correlation within routes.[32] Overall, this approach allows me to control for the seasonal variation at the tax implementation date and interpret β_2 as the effect of the tax, on top of whatever is generated by seasonal variations.

The empirical strategy outlined above hinges on the assumption that seasonality has on average the same effect across years, and Sample 18-19 can serve as a counterfactual for what would have happened to the outcomes considered absent the tax.[33] Testing the validity of this assumption entails verifying that the parallel-trend assumption is satisfied. To that end, I use an event study through which I test whether there are statistically significant differences in the outcomes across Sample 18-19 and Sample 19-20 in each of the weeks before the focal dates (i.e., before period 0).[34] The event study

[31] In other words, $Post_t$ equals one for observations in Sample 19-20 and after January 6, 2020 or for observations in Sample 18-19 and after January 7, 2019.

[32] The main results remain robust to clustering at alternative levels.

[33] In principle, trips occurring during off-peak times (i.e., weekends or nighttime) were also candidate control groups to identify the effect of the tax. However, due to the structure of the tax, this approach would not allow me to determine the impact of the tax on non-downtown rides, similar to the challenge that would arise using non-downtown rides as a control for downtown trips. Additionally, I verified that off-peak time rides exhibit distinct riding patterns, further indicating their unsuitability as control groups.

[34] In practice, I take the week right before the focal date in each subsample (i.e., period -1) as the benchmark and replace $\beta_2 \cdot \left(Sample1920_{i,h,j} \times Post_t\right)$ in Equation 1 with $\sum_{k \neq -1} \gamma_k \cdot \left(Sample1920_{i,h,j} \times D_{k,t}\right)$, where $k \in \{-6, ..., 6\}$ and $D_{k,t}$ equals one if period t falls in the kth week around period 0. The details of this specification are discussed in Appendix B.

also allows me to analyze differences between Sample 18-19 and Sample 19-20 in each of the seven weeks after the tax was implemented, thereby assessing its dynamic effects. This is particularly interesting when examining how the pricing algorithm of TNPs reacts to the tax.

I conduct three additional sets of robustness checks, which I describe in detail in Appendix B. First, I assess the robustness of my findings to different sample construction procedures. Second, I examine the effects of the tax on additional price metrics and alternative measures of congestion to further test the robustness of the findings. Third, Figure 3 points to a potential concern regarding the non-stationarity of ride-sharing prices over the study period. While the event study design already tackles this concern, I further validate my approach by augmenting Equation 1 with a linear trend representing calendar weeks.

6. The Effects of the Tax

This section studies the impact of the tax on the taxi and ride-sharing industry. First, I describe how the tax affected the price of ride-sharing and taxis for different types of rides, estimating the tax pass-through rate. Next, I examine the effects on the number of pickups completed by TNPs and taxis. Finally, I study the impact of the tax on congestion across different areas of Chicago.

6.1. Change in Prices and Tax Pass-Through

I begin by investigating how TNPs responded to the tax. I do so by estimating Equation 1 using as dependent variable the price (in logs) of the four types of rides considered: downtown single rides, which in my final sample faced a \$2.28 tax increment, other single rides and downtown shared rides, which both faced a \$0.53 tax increment, and other shared rides, for which the tax decreased by \$0.07.

The first two rows of Table 3 report the estimates of β_1 and β_2 obtained through these regressions. In the downtown market, column (1) shows that the prices of single rides in Sample 19-20 are 4.40% lower but the tax led to a large (and significant at 5% level) increase by 12.29%. For a ride of this kind, this implies an increase in the average price from about \$19.20 to roughly \$21.50. Column (3) shows that the tax increased prices for shared rides by approximately 5.65%, translating to an average fare increase of about \$0.72.

For what concerns non-downtown rides, namely those starting and ending outside the downtown area, column (2) shows that the price of single rides increased by 3.25%. Although smaller than for downtown single rides, this represents an important change in the market, implying an average raise in the level of these prices by more than $0.53. Column (4) shows that even if the tax on shared trips went down, the price increased by 1.82%, corresponding to a growth of about $0.22 per trip, on average.[35]

TABLE 3. The effect of the tax on TNP prices

	(1) Single downtown	(2) Single other	(3) Shared downtown	(4) Shared other
Sample1920	-0.045***	0.005	-0.023	0.027***
	(0.014)	(0.005)	(0.029)	(0.007)
Sample1920 × Post	0.116***	0.032***	0.055***	0.018***
	(0.006)	(0.003)	(0.008)	(0.005)
Observations	127,700	1,581,150	107,321	1,229,076
Adj. R-sq	0.910	0.908	0.731	0.715
Route FE	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓
Period FE	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column describes the effect of the tax on the price (in logs) of different types of TNP rides (columns 1 to 4) or taxi rides (columns 5 and 6). All regressions include controls for weather and the distance of the trip (in miles). Standard errors are two-way clustered at the route-date level and reported in parentheses.

While the regressions control for average trip distance, I also verify that the tax did not induce meaningful changes in this dimension of trip composition. Table C.2 in the Appendix shows that the average distance of TNP rides remained largely stable after the tax. Even when differences are statistically significant in some specifications, their magnitudes are very small, suggesting that compositional shifts are unlikely to explain

[35] Appendix B shows that the results in Table 3 are robust to the retention in the sample of all weeks dropped in the final sample and to the addition of a linear trend for the calendar week in Equation 1 that accounts for the non-stationarity of ride-sharing prices over the study period. Moreover, Columns (1) and (2) of Table D.2 show that results for trips starting or ending in the border area are in line with those of Table 3.

the observed price effects. These findings support the interpretation that the observed price patterns are not primarily driven by changes in the types of trips taken.[36,37]

Typically, the pass-through rate of a tax can be calculated by dividing the price change due to the tax by the tax increment (Weyl and Fabinger 2013). However, in the context of ride-sharing, riders may substitute single rides for shared ones based on their relative prices. To account for the asymmetry in the Chicago tax schedule, I estimate the average pass-through rate for each market (downtown and non-downtown) as:

$$\frac{q_0^{\text{single}} \Delta P^{\text{single}} + q_0^{\text{shared}} \Delta P^{\text{shared}}}{q_0^{\text{single}} \Delta \tau^{\text{single}} + q_0^{\text{shared}} \Delta \tau^{\text{shared}}}, \tag{2}$$

where ΔP^k represents the change in the level for ride type $k = \{\text{single, shared}\}$, $\Delta\tau^k$ is the corresponding tax increment, and q_0^k is the average number of daily rides of type k before the tax. Moreover, given the estimates $\hat{\beta}_2^k$ of β_2 reported in Table 3 and the average price (in \$) of a given type of ride before the tax p_0, ΔP^k is computed as $\left[\exp(\hat{\beta}_2^k) - 1\right] \cdot p_0^k$. Standard errors are obtained by estimating a pooled regression, algebraically equivalent to Equation 1, for each market and then applying the delta method. A bootstrap procedure that re-estimates separate regressions for single and shared rides in each market yields similar results.[38] The point estimates suggest overshifting of the tax, with average pass-through of 104% in the downtown market and 124% outside downtown. The corresponding 95% confidence intervals ([0.93, 1.16] downtown; [0.99, 1.49] outside) indicate that riders essentially bore the full burden of the tax, and possibly more—particularly outside downtown. The relatively lower pass-through rate downtown is consistent with heterogeneity in demand elasticities across geographic markets, as the ease of accessing alternative transportation options may vary depending on whether one endpoint of the trip is the downtown zone. For instance, public transit is often more convenient when one endpoint is downtown, which could make demand for downtown single rides more elastic and thereby reduce pass-through.

To illustrate the gap between my empirical findings and a standard benchmark, I

[36] Consistently, the top panel of Table B.4 shows results that align with Table 3 when using price per mile as the dependent variable.

[37] Although the tax did not apply to traditional taxis and their fares are regulated, changes in trip composition could still indirectly affect the average price of a taxi ride. However, Table C.2 shows no substantial changes in average taxi trip distance, and Table C.1 confirms that changes in taxi prices are either statistically insignificant or, when significant, economically minor (below 1%).

[38] Since for non-downtown shared rides the tax was reduced, I also verify that this is not driving the high pass-through by repeating the analysis under the assumption that there was no tax change for shared trips outside downtown.

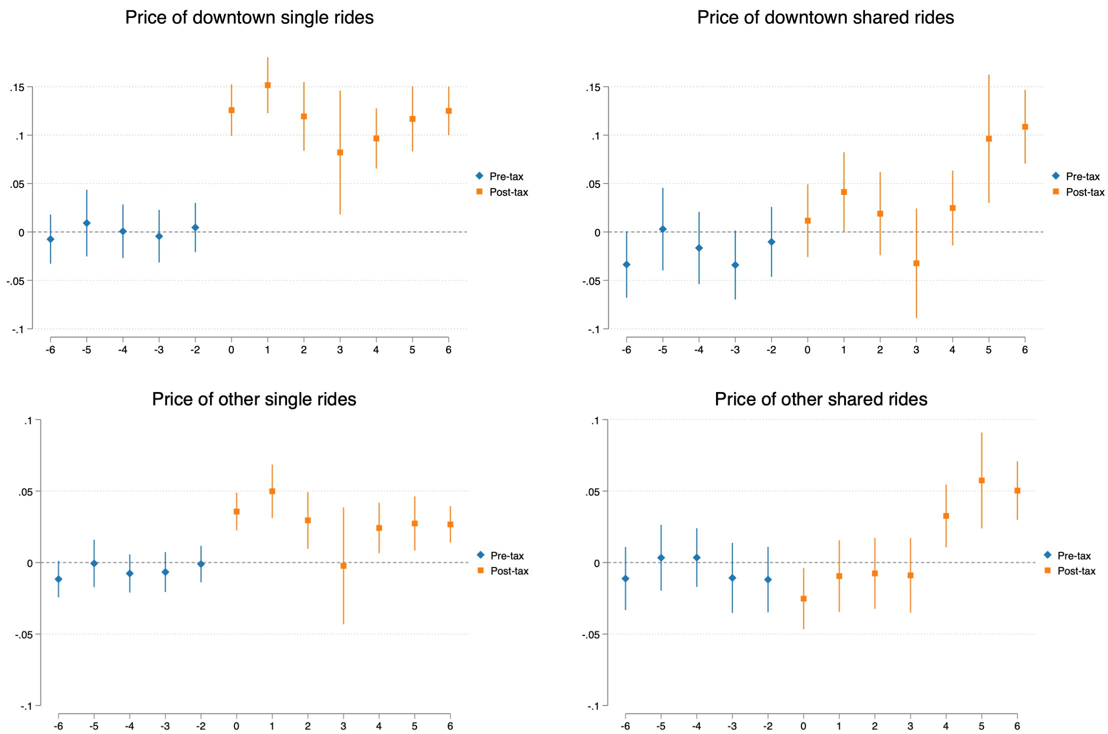
provide a back-of-the-envelope calculation of the pass-through rate ρ in a perfectly competitive setting, using the formula $\rho = \frac{1}{1+(\varepsilon_D/\varepsilon_S)}$ (Weyl and Fabinger 2013), where $\varepsilon_D \equiv -\left(D'\frac{P}{Q}\right)$ and $\varepsilon_S \equiv S'\frac{P}{Q}$ denote the price elasticities of demand and supply, respectively. Drawing on estimates from the literature—demand elasticities between 0.4 and 0.6 (Cohen et al. 2016) and a median labor supply elasticity of 1.92 (Chen et al. 2019)—the implied pass-through rate under perfect competition would be lower than 83%, well below that implied by the empirical estimates reported in Table 3.[39] Drawing on estimates from the literature—demand elasticities between 0.4 and 0.6 (Cohen et al. 2016) and a median labor supply elasticity of 1.92 (Chen et al. 2019)—the implied pass-through rate would be lower than 83%, well below the estimates discussed above.

Complete pass-through and even tax over-shifting can be rationalized by the existence of market power combined with some strict assumptions on the shape of demand and market conduct. In Section 2, I outlined several mechanisms that could also contribute to the high pass-through observed in the context of ride-sharing. First, indirect network effects between riders and drivers may amplify price responses if reduced demand also discourages drivers from supplying rides. Second, platforms may internalize substitution between single and shared rides, adjusting prices across both services. While these channels are consistent with the observed outcomes, the available data do not allow them to be separately identified.

The next section provides evidence consistent with substitution within ride-sharing services, but concentrated exclusively in the downtown area. This suggests that substitution alone appears insufficient to explain the broader pattern of overshifting. Moreover, because the TNP dataset lacks driver identifiers, I cannot directly test supply-side adjustments. Still, aggregate monthly data in Figure C.1 show that the gap in driver participation between Sample 19–20 and Sample 18–19 narrowed after the tax was implemented. This pattern is suggestive of a supply response, but not conclusive. Other unobserved forces—such as platforms' ability to adjust the effective wage paid to drivers, or reputational strategies whereby platforms set prices to signal that new taxes burden consumers—may also have contributed to the observed outcomes. Taken together, these considerations highlight how the high pass-through rates documented may reflect the interaction of multiple mechanisms.

[39] Absent network externalities, and thus changes in the number of drivers following the tax, the number of rides supplied is proportional to the hours worked by a driver, i.e., $S = L \cdot \sigma(L) \cdot h(p) = \kappa \cdot h(p)$. In this case, price changes affect supply only through their effect on hours worked, so that $\varepsilon_S \equiv S'\frac{P}{Q} = \kappa h'\frac{P}{Q} = h'\frac{P}{h} \equiv \varepsilon_h$, where ε_h is the labor supply elasticity.

FIGURE 4. Dynamic effect of the tax on TNP prices



Notes: Each figure plots the coefficients that summarize the dynamic impact of the tax on the price (in logs) of different types of TNP rides with 95% confidence intervals. The x-axis displays the number of weeks since the implementation of the tax for observations belonging to *Sample 19-20*, or since January 7, 2019 for all the other observations. All regressions include controls for weather, as well as for the distance of the trip (in miles). Standard errors are two-way clustered at the route-date level.

To gain a better understanding of the dynamics that led to the observed average change in prices in the seven weeks after the tax implementation, I adopt an event study design. The diamond markers in all four sub-figures of Figure 4 suggest that the trend in TNP prices was similar across Sample1819 and Sample1920 in the weeks before the one coinciding with the policy implementation. The squared markers instead illustrate the point estimates of the impact—with 95% confidence intervals—of the tax on the price (in logs) of different types of TNP rides in each of the weeks after the tax began.

The top left panel of Figure 4 illustrates that following the implementation of the tax, prices for downtown single rides initially rose, then experienced a slight decline before rising again. However, they consistently remained between 7.5% and 16% higher than what they would have been absent the tax. A similar trend is observed in the bottom left panel for single rides outside downtown, albeit with a smaller percentage increase due to the lower tax increment. These two plots imply a significant and lasting influence of the tax on the prices of single rides.

The top right panel of Figure 4 illustrates the price trend for downtown shared rides. After the tax was introduced, prices rose, with a pronounced surge in the last two weeks of the sample, exceeding a 10% increase. This pattern may reflect a delayed adjustment in labor supply driven by network effects. For non-downtown shared rides, the bottom right panel of Figure 4 indicates that the average effect estimated in Table 3 was primarily driven by the increase in prices that occurred five weeks after the tax's implementation. The figure reveals an adjustment trend, where prices initially fell by 2.5% after the small tax reduction of $0.07 per trip but subsequently rose due to the decrease in the supply of rides, ultimately leading to a sustained price increase.

To avoid potential data contamination caused by COVID-19, I focus on the effects of the tax during the seven weeks immediately following its implementation. A natural question arises as to how these short-run estimates relate to and inform the long-run implications of the policy. In the context of a tax on ride-sharing, the time required for the market to reach the long-run equilibrium is uncertain, as is whether the long-run equilibrium will differ significantly from the short-run one. Notably, such differences could emerge due to slower adjustments on the supply side. For example, drivers may modify their hours worked only after observing changes in earnings, and decisions to join or leave the platform may take even longer.

Hall, Horton and Knoepfle (2021) document the transition to the new long-run equilibrium following an increase in Uber prices, showing that drivers respond to the increase in earnings per hour by working more. This—combined with the reduction in demand for Uber due to the higher prices—reduces prices until, in about eight weeks, the market reaches a new equilibrium wherein drivers earn roughly the same amount per hour as before the price increase and riders face higher prices. Assuming a similar adjustment process applies in my context, where I analyze seven weeks after the tax, would suggest that my short-run estimates may reasonably approximate long-run outcomes.

Nonetheless, without examining a longer period after the tax, I cannot rule out the possibility that the long-run effects of the tax differ from those estimated in this paper. Even if this is the case, documenting the short-term effects remains valuable for several reasons. First, short-term responses of platforms and riders to the tax shed light on the adjustment process toward the long-run equilibrium, offering insights into key aspects of demand and supply (Hindriks and Serse 2019). Second, to the extent that supply-side adjustments occurred during the seven weeks post-tax, my estimates may provide valuable insights into the longer-run effects of the tax. Third, short-term changes can have significant welfare implications, particularly if the transition to the long-run equilibrium takes considerable time. If my estimates do not yet reflect the long-run equilibrium, this would suggest that the adjustment period extends beyond seven weeks, thus emphasizing the importance of documenting the short-term effects of the policy.

6.2. The Impact on Ride-sharing and Taxi Pickups

Section 2 illustrates how changes in the final price paid by riders for single and shared TNP rides can influence their choice of transportation mode, potentially driving them to substitute within ride-sharing services or switch to traditional taxi services.[40]

Table 4 displays the results derived from estimating Equation 1, with the number of various types of TNP rides (columns (1)-(4)) and taxi rides (columns (5)-(6)) serving as the dependent variable. Since the tax may influence the number of trips along both the intensive and extensive margins, I follow the approach proposed by Chen and Roth (2023) and estimate the model using Poisson Pseudo-Maximum Likelihood (PPML). This method accommodates the count nature of the data and provides consistent estimates of the conditional mean, even in the presence of overdispersion and a large number of zero-valued observations (Silva and Tenreyro 2006).

Regarding downtown rides, Column (1) indicates that the tax resulted in a 10.60% reduction in single TNP pickups downtown. Simultaneously, Columns (3) reveals that downtown rides were partially diverted to shared TNP rides, which experienced a large and statistically significant uptick (25.60%), despite the 5.65% price hike. The considerably larger market share of single rides relative to shared ones, shown in Table 2, implies that the rise in shared service usage did not offset the decline in single rides. For what concerns the non-downtown rides, my results indicate a similar reduction in the number of single TNP trips, but, differently from what happened for downtown rides, I do not find evidence of an increase in usage of the shared service. The heterogeneity in substitution patterns across different areas of Chicago can be attributed to factors such as differing demand for single versus shared rides, variations in demand density that facilitate ride pooling downtown, and the higher downtown tax, which led riders with a relatively higher willingness to pay—those more inclined to choose shared rides over cheaper options like public transit—to shift away from single rides.

[40] As the data does not specify the ride-sharing company providing the ride (e.g., Uber, Lyft, or Via), I can only analyze sector-level substitutions between taxis and TNP services, which is however the main focus of this paper.

TABLE 4. The effect of the tax on the number of pickups

	TNP				Taxi	
	(1) Single downtown	(2) Single other	(3) Shared downtown	(4) Shared other	(5) Downtown	(6) Other
Sample1920	0.351*	0.269***	-0.546***	-0.558***	1.436	-0.069
	(0.203)	(0.072)	(0.166)	(0.058)	(1.223)	(0.192)
Sample1920 × Post	-0.112***	-0.151***	0.228***	-0.018	0.064	-0.013
	(0.014)	(0.011)	(0.031)	(0.018)	(0.047)	(0.021)
Observations	160,160	5,649,280	160,160	5,542,160	160,160	4,806,880
Route FE	✓	✓	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table reports the results of the PPML regressions used to estimate the effect of the tax on the number of different types of rides. Columns (1) to (4) describe the effect on the four types of TNP rides considered, whereas the last two columns refer to the effect on the number of downtown and non-downtown taxi rides. All regressions include controls for weather. Standard errors are two-way clustered at the route-date level and reported in parentheses.

An important question about the tax revolved around the degree to which it would benefit taxis. This bears significance given the policy debate regarding the depreciation of taxi medallions' value which followed the rise of ride-sharing services. Column (5) of Table 4 shows only a very modest and statistically insignificant shift toward traditional taxis downtown. Column (6) also indicates no statistically significant effect for the number of non-downtown taxi pickups. Thus, I conclude that the tax had no economically and statistically significant impact on the number of trips completed by traditional taxis.

Overall, these findings highlight the importance of riders substituting between different ride-sharing services, while indicating a minor role played by substitution with traditional taxis. This has important implications for TNP pricing and congestion. My results also imply a decrease in the total number of trips across taxis and ride-sharing services after the tax, suggesting a potential shift toward other transportation options, such as public transit or private vehicles, which could have opposite effects on congestion.

A significant decrease in tipping is another potential mechanism—alongside substitution towards public transit or private vehicles—that could explain the limited shift away from ride-sharing. Panel B of Table B.4 in the Appendix shows that tips remained stable for downtown rides and decreased slightly for non-downtown rides, though this effect was modest. Thus, while there was a shift in tipping behavior, especially given that tips are generally a percentage of the ride price, my findings suggest that this mechanism is unlikely to be a primary driver of the observed limited substitution.

6.3. The Impact on Congestion

One of the City of Chicago's stated motivations for taxing ride-sharing was its role in exacerbating traffic congestion, particularly in the downtown area. The documented decrease in the number of TNP single rides downtown and the simultaneous increase in shared TNP ride usage achieved through the tax, might offer the potential benefit of alleviating congestion by reducing the number of vehicles on the streets.

Since the primary focus is on determining whether the tax effectively reduced congestion in specific areas of the city, I categorize trips into six segments based on the three macro-areas of the city defined in Section 4 (downtown, border, and other): (i) trips where both endpoints are within the downtown zone, which I refer to as trips in the "Downtown-Downtown" (DD) segment; (ii) trips connecting downtown to border areas, which I refer to as trips in the "Downtown-Border" (DB) segment; (iii) trips connecting downtown to any other area, which I refer to as trips in the "Downtown-Other" (DO) segment; (iv) trips where both endpoints are within border areas, which I refer to as trips in the "Border-Border" (BB) segment; (v) trips connecting border areas to any other non-downtown area, which I refer to as trips in the "Border-Other" (BO) segment; and (vi) all other trips. It is important to note that for (i)-(iii), the tax increment in my sample amounts to $2.28 for single rides and $0.53 for shared rides, while for (vi), it amounts to $0.53 for single rides and -$0.07 for shared rides. For trips falling into categories (iv) and (v), I cannot identify the exact tax on single and shared rides, as it could be either of those mentioned above.

To measure traffic congestion, I consider two possible proxies. The former is simply the average speed (in mph) of a TNP vehicle. Mangrum and Molnar (2017) rely on a similar strategy with taxi trip records to measure historical street-level speed in NYC, and use it as a proxy for congestion. Naturally, measuring congestion solely through speed presents several challenges due to its inability to capture various nuances of traffic conditions. For example, speed alone does not reflect the overall flow and density of traffic, as congestion can occur even at high speeds if traffic volume is excessive. To account for this, I define traffic congestion as the travel time or delay in excess of that normally incurred under free-flow travel conditions (Lomax 1997). Specifically, I

Table 5. Congestion measures before the tax

	Downtown-Downtown		Downtown-Border		Downtown-Other		Border-Border		Border-Other		Other	
	(1) mean	(2) sd	(3) mean	(4) sd	(5) mean	(6) sd	(7) mean	(8) sd	(9) mean	(10) sd	(11) mean	(12) sd
Trip miles	1.519	0.689	2.378	0.835	10.04	4.490	2.248	1.075	9.930	4.572	7.358	5.850
Trip minutes	8.327	1.854	11.71	2.648	27.77	11.47	10.26	4.055	27.61	11.41	21.13	13.44
Travel Rate (minutes/mile)	6.101	1.872	5.309	1.534	2.992	1.028	4.932	1.413	3.021	1.009	3.422	1.237
Trip speed (mph)	11.22	5.296	12.33	3.882	22.52	8.320	13.30	4.305	22.29	8.352	20.45	35.56
Trip speed (mph, logs)	2.439	0.332	2.552	0.272	3.104	0.325	2.620	0.277	3.093	0.324	2.985	0.363
Delay Rate (minutes/mile)	2.448	2.044	2.636	1.566	1.205	0.957	2.276	1.434	1.272	0.928	1.161	1.126

Notes: The table presents summary statistics at the route-hour level for each of the six segments considered. The data refers to the weeks before the implementation of the tax in Sample 19-20. The delay rate is computed as the difference between the actual and acceptable travel rate.

approximate traffic congestion with the delay rate, defined as:

$$\text{DR}^* = \text{TR} - \text{TR}_{acc}, \tag{3}$$

where TR is the actual travel rate, i.e., the average minutes per mile of a TNP ride, and TR_{acc}, is the acceptable travel rate, which I compute, for each calendar date in my sample, as the 15^{th} percentile of the TR during off-peak times.[41] It is essential to highlight that the delay rate, while a valuable metric, is not flawless. In particular, it may overlook congestion in areas with high traffic volume but relatively insignificant delays. Moreover, its effectiveness relies on defining the acceptable travel rate, which can be challenging to determine.

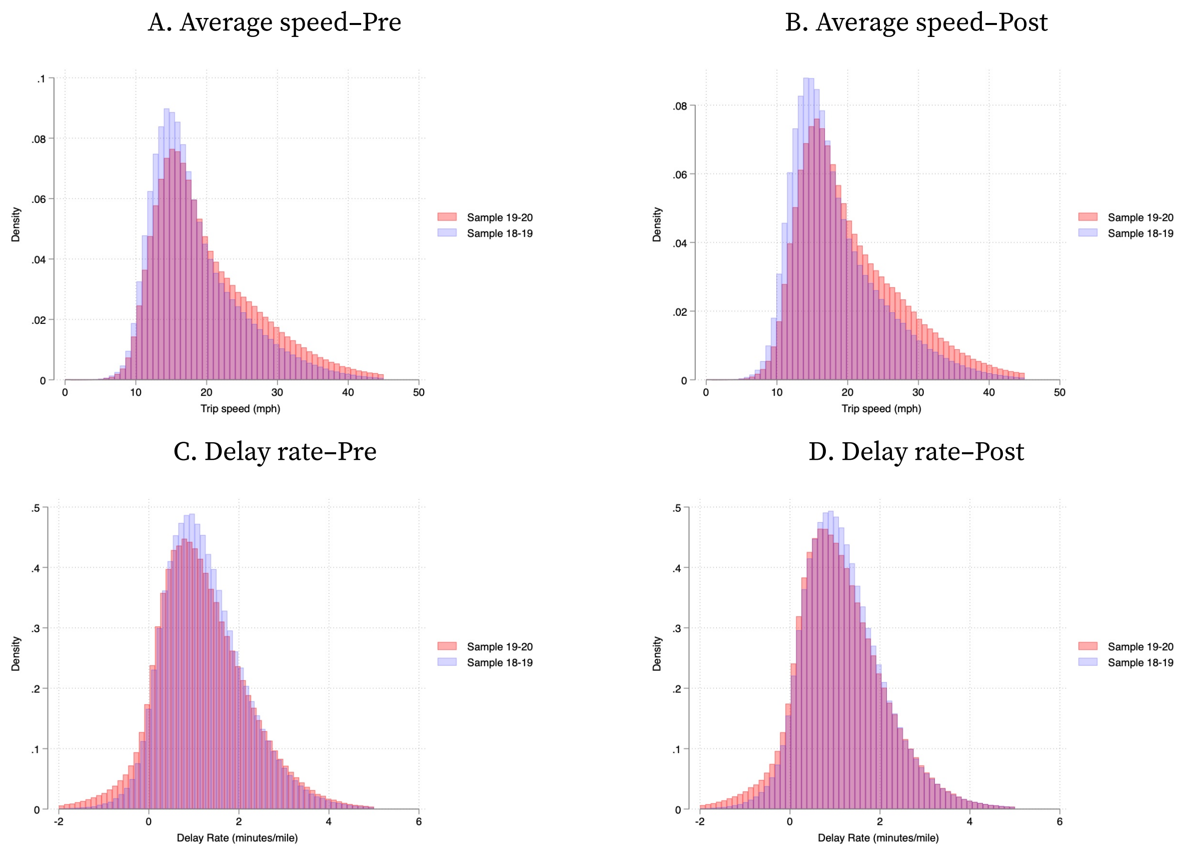
In constructing my measures of congestion, I only use TNP trips to control for compositional changes in the share of trips completed by TNPs versus taxis. If I also included taxi trips, then a change in the share of trips completed by each type of vehicle after the tax would lead to comparing the outcomes of potentially different types of vehicles before and after the tax. I focus on TNP rather than taxi trips because they account for the vast majority of trips in Chicago.[42]

Table 5 presents summary statistics for each of the six segments analyzed in the weeks leading up to the implementation of the tax in Sample 19-20. It is notable that

[41]My approach to measuring TR_{acc} builds on the one followed by the Texas Transportation Institute at The Texas A&M University System, in the 2005 white paper titled "The Keys to Estimating Mobility in Urban Areas," available at: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=d7fee6b8536c37873057dfea6b733142c8a8842b. Table B.5 in the appendix shows the robustness of my results to using alternative definitions of the acceptable travel rate.

[42]Moreover, the amount earned by a taxi driver from a given ride depends on the length of that ride, whereas the price of a TNP ride is set before the ride. This implies that, conditional on having picked up a passenger, a taxi driver's speed is more likely to be affected by demand conditions, which may have changed after the tax.

FIGURE 5. Distribution across subsamples before and after the focal dates



Notes: The figures plot the distribution of the average speed or delay rate for any trip before or after the focal dates (January 7, 2019 for Sample 18-19 and January 6, 2020 for Sample 19-20) separately for each subsample (Sample 18-19 and Sample 19-20).

trips within the Downtown zone (DD segment) tend to cover shorter distances at slower speeds. During peak times, the average speed is just above 11 mph, and it takes over 6 minutes on average to cover a mile. This is approximately 2 minutes and 30 seconds longer than what would be expected under free-flow conditions. When comparing these statistics with the measures of traffic congestion in segments where at least one endpoint is definitely outside the downtown zone as defined by the city (i.e., DO, BO, and Other), it becomes clear that congestion is much more pronounced in the downtown area.

Figure 5 illustrates the distribution of congestion measures across subsamples both before and after the focal dates (period 0 in the DiD framework). The gap between the two distributions appears similar before and after the focal dates, which suggests the absence of a significant reduction in congestion, although the figures do not differentiate among segments.

Table 6. The effect of the tax on congestion

	(1) Downtown-Downtown	(2) Downtown-Border	(3) Downtown-Other	(4) Border-Border	(5) Border-Other	(6) Other
Dep. Var. : Average speed (logs, mph)						
Sample1920	-0.740***	-0.172***	0.012	0.031***	0.057***	0.066***
	(0.008)	(0.006)	(0.037)	(0.005)	(0.017)	(0.010)
Sample1920 × Post	0.081***	0.031***	0.017*	0.031***	0.019*	0.023***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.007)
Observations	4,111	8,189	224,670	12,451	441,364	2,810,250
Adj. R-sq	0.704	0.532	0.596	0.507	0.570	0.437
Dep. Var. : DR*						
Sample1920	1.767***	0.799***	-0.030	0.058	-0.074**	-0.035*
	(0.124)	(0.047)	(0.060)	(0.043)	(0.029)	(0.018)
Sample1920 × Post	-0.563***	-0.033	-0.006	0.024	-0.017	-0.025
	(0.163)	(0.078)	(0.035)	(0.071)	(0.035)	(0.025)
Observations	4,111	8,189	224,664	12,451	441,355	2,809,393
Adj. R-sq	0.375	0.484	0.480	0.408	0.451	0.194
Route FE		✓	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column summarizes the results of a specification relative to one of the six segments considered. In the top panel, the dependent variable is the logarithm of the average speed (in mph), whereas in the bottom panel, the dependent variable is the Delay rate. Standard errors are two-way clustered at the route-date level and reported in parentheses. The Route FE is absent in Column (1) as there is only one route in the DD segment.

To formally study the impact of the tax on average speed and delay rates across the six defined segments, I employ Equation 1 once again and run six distinct regressions—one per segment—for each dependent variable. The results are presented in Table 6. In the upper panel, it is evident that average speed increased across all segments, with statistically significant enhancements ranging from 2.3% to 8.4%. The most substantial improvement, reaching almost 1 mph, was observed in DD trips, which were arguably the primary focus of the tax. Moreover, the policy's higher effectiveness downtown may be explained by riders' outside options: switching to transit is easier if one endpoint of the trip is within downtown, making it more likely that a reduction in ride-sharing trips results in fewer vehicles on the streets.

From a policy standpoint, delay rates are conceivably a more relevant metric as they directly measure the time savings attributed to the intervention. While the tax marginally reduced delay rates across most segments, the statistically significant effect was only observed in DD trips. These trips experienced an average time savings of approximately 34 seconds per mile, translating to about 51 seconds per trip, on average. Consequently, the congestion-alleviating benefits of the tax appear concentrated on trips that both originate and end within Chicago's central business district, while the overall magnitude of the improvement remains relatively modest.[43] As a benchmark, using ride-sharing data, Buchholz et al. (2020) estimate the average value of time to be \$13.47 per hour, although it can vary significantly among individuals. Based on this, the tax would yield an average saving of approximately \$0.19 per trip for ride-sharing users, which appears relatively low compared to the magnitude of the tax increment and the resulting rise in ride-sharing prices.[44]

Overall, the documented impact of the tax on traffic congestion suggests that the rise of ride-sharing companies is not solely responsible for exacerbating congestion. Therefore, implementing congestion pricing schemes that also target taxis and private vehicles might yield more effective results.

7. Conclusion

This paper examines the effects of a targeted tax on ride-sharing platforms using trip-level data from the City of Chicago. I document the extent to which the tax is passed through to riders, analyze its impact on competitive dynamics with traditional taxis, and assess its potential to mitigate urban congestion, which represents a major urban mobility challenge and a key negative externality often associated with ride-sharing.

The analyses generate three main sets of results. First, I estimate how ride-sharing platforms adjust their prices in response to transaction taxes. I find that the prices of both single and shared TNP rides significantly increased, with point estimates of average tax pass-through rate above 100%. While substitution across services helps explain this pattern, it does not fully account for the extent of the price response. This suggests that other forces, such as platform market power or indirect network effects between drivers and riders, may have also contributed to the observed outcomes. Second, while higher prices decreased ride-sharing usage, this effect was partially offset in downtown Chicago by riders substituting single with shared rides. Additionally, the tax did not

[43] On weekdays, congestion may be more severe during rush hours, and there could be particular interest from policymakers in alleviating traffic congestion during these times. Thus, in Table C.3, I also present evidence indicating that the benefits of the tax were not significantly greater during rush hours.

[44] These calculations reflect only the direct benefits to ride-sharing users and do not account for potential congestion relief accruing to other road users (private vehicles, taxis, public transit), which may be larger but cannot be quantified without citywide traffic flow data.

significantly shift demand back to taxis. Lastly, while the tax encouraged the usage of shared rides downtown, its impact on reducing traffic congestion remained modest.

The analyses presented in this article shed light on the potential drawbacks of taxes targeting platforms competing with regulated incumbents. They suggest how such taxes could result in a significant increase in prices, primarily borne by platforms' users. Furthermore, my analyses also indicate that these policies may not be as effective as expected in leveling the playing field between platforms and regulated incumbents, nor in tackling the negative externalities associated with platforms, such as congestion in the context of ride-sharing. However, it is important to note that tax incidence analysis is just the initial step in understanding the welfare implications of these taxes. For a more comprehensive welfare analysis and to explore optimal tax policies, a detailed structural model is essential. The availability of public data and the relevance of the tax on ride-sharing make Chicago an extraordinary laboratory to go down this route.

References

Abraham, Katharine G, John C Haltiwanger, Claire Hou, Kristin Sandusky, and James R Spletzer. 2021. “Driving the gig economy.” *Unpublished paper, National Bureau of Economic Research. Accessed June,* 25: 2019.

Agrawal, David R., and Weihua Zhao. 2023. “Taxing Uber.” *Journal of Public Economics,* 221: 104862.

Agrawal, David R, and William H Hoyt. 2019. “Pass-through in a multiproduct world.” *Available at SSRN 3173180.*

Almagro, Milena, Felipe Barbieri, Juan Camilo Castillo, Nathaniel G Hickok, and Tobias Salz. 2024. “Optimal Urban Transportation Policy: Evidence from Chicago.” National Bureau of Economic Research Working Paper 32185.

Alonso-González, María J., Oded Cats, Niels van Oort, Sascha Hoogendoorn-Lanser, and Serge Hoogendoorn. 2021. “What are the determinants of the willingness to share rides in pooled on-demand services?” *Transportation,* 48(4): 1733–1765.

Anderson, Michael L. 2014. “Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion.” *American Economic Review,* 104(9): 2763–96.

Anderson, Simon P., André de Palma, and Brent Kreider. 2001. “Tax incidence in differentiated product oligopoly.” *Journal of Public Economics,* 81(2): 173–192.

Bagchi, Sutirtha. 2018. “A tale of two cities: an examination of medallion prices in New York and Chicago.” *Review of Industrial Organization,* 53(2): 295–319.

Belleflamme, Paul, and Eric Toulemonde. 2018. “Tax incidence on competing two-sided platforms.” *Journal of Public Economic Theory,* 20(1): 9–21.

Besanko, David, Jean-Pierre Dubé, and Sachin Gupta. 2005. “Own-brand and cross-brand retail pass-through.” *Marketing Science,* 24(1): 123–137.

Besley, Timothy. 1989. “Commodity taxation and imperfect competition: A note on the effects of entry.” *Journal of Public Economics,* 40(3): 359–367.

Besley, Timothy J., and Harvey S. Rosen. 1999. “Sales Taxes and Prices: An Empirical Analysis.” *National Tax Journal,* 52(2): 157–178.

Bibler, Andrew J., Keith F. Teltser, and Mark J. Tremblay. 2021. “Inferring tax compliance from pass-through: Evidence from Airbnb tax enforcement agreements.” *Review of Economics and Statistics,* 103(4): 636–651.

Bourreau, Marc, Bernard Caillaud, and Romain De Nijs. 2018. “Taxation of a digital monopoly platform.” *Journal of Public Economic Theory,* 20(1): 40–51.

Buchholz, Nicholas. 2021. “Spatial Equilibrium, Search Frictions, and Dynamic Efficiency in the Taxi Industry.” *The Review of Economic Studies,* 89(2): 556–591.

Buchholz, Nicholas, Laura Doval, Jakub Kastl, Filip Matějka, and Tobias Salz. 2020. “The value of time: Evidence from auctioned cab rides.” National Bureau of Economic Research.

Castillo, Juan Camilo. 2020. “Who benefits from surge pricing?” *Available at SSRN 3245533.*

Castillo, Juan Camilo, Daniel T. Knoepfle, and E. Glen Weyl. 2022. “Matching in ride hailing: Wild goose chases and how to solve them.” *Available at SSRN 2890666.*

Chen, Jiafeng, and Jonathan Roth. 2023. “Logs with Zeros? Some Problems and Solutions*.” *The*

Quarterly Journal of Economics, 139(2): 891–936.

Chen, M. Keith, Judith A. Chevalier, Peter E. Rossi, and Emily Oehlsen. 2019. "The Value of Flexible Work: Evidence from Uber Drivers." *Journal of Political Economy,* 127(6): 2735–2794.

Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. 2016. "Using Big Data to Estimate Consumer Surplus: The Case of Uber." National Bureau of Economic Research Working Paper 22627.

Delipalla, Sofia, and Michael Keen. 1992. "The comparison between ad valorem and specific taxation under imperfect competition." *Journal of Public Economics,* 49(3): 351–367.

Doyle, Joseph J., and Krislert Samphantharak. 2008. "$2.00 Gas! Studying the effects of a gas tax moratorium." *Journal of Public Economics,* 92(3): 869–884.

Einav, Liran, Chiara Farronato, and Jonathan Levin. 2016. "Peer-to-Peer Markets." *Annual Review of Economics,* 8(1): 615–635.

Farronato, Chiara, and Andrey Fradkin. 2022. "The Welfare Effects of Peer Entry: The Case of Airbnb and the Accommodation Industry." *American Economic Review,* 112(6): 1782–1817.

Fréchette, Guillaume R., Alessandro Lizzeri, and Tobias Salz. 2019. "Frictions in a Competitive, Regulated Market: Evidence from Taxis." *American Economic Review,* 109(8): 2954–92.

Fullerton, Don, and Gilbert Metcalf. 2002. "Tax incidence." In *Handbook of Public Economics*. Vol. 4. 1 ed., , ed. A. J. Auerbach and M. Feldstein, 1787–1872. Elsevier. Section: 26.

Gorodnichenko, Yuriy, and Oleksandr Talavera. 2017. "Price Setting in Online Markets: Basic Facts, International Comparisons, and Cross-Border Integration." *American Economic Review,* 107(1): 249–82.

Gurran, Nicole, and Peter Phibbs. 2017. "When tourists move in: how should urban planners respond to Airbnb?" *Journal of the American planning association,* 83(1): 80–92.

Hall, Jonathan V., John J. Horton, and Daniel T. Knoepfle. 2021. "Pricing in Designed Markets: The Case of Ride-Sharing." Unpublished.

Hamilton, Stephen F. 1999. "Tax incidence under oligopoly: a comparison of policy approaches." *Journal of Public Economics,* 71(2): 233–245.

Hindriks, Jean, and Valerio Serse. 2019. "Heterogeneity in the tax pass-through to spirit retail prices: Evidence from Belgium." *Journal of Public Economics,* 176: 142–160.

Katz, Michael L., and Harvey S. Rosen. 1985. "Tax Analysis in an Oligopoly Model." *Public Finance Quarterly,* 13(1): 3–20. Publisher: SAGE Publications.

Kenkel, Donald S. 2005. "Are Alcohol Tax Hikes Fully Passed Through to Prices? Evidence from Alaska." *American Economic Review,* 95(2): 273–277.

Klein, Tobias J, Martin Salm, and Suraj Upadhyay. 2022. "The response to dynamic incentives in insurance contracts with a deductible: Evidence from a differences-in-regression-discontinuities design." *Journal of Public Economics,* 210: 104660.

Kotlikoff, Laurence J., and Lawrence H. Summers. 1987. "Chapter 16 Tax incidence." In *Handbook of Public Economics*. Vol. 2 of *Handbook of Public Economics,* 1043–1092. Elsevier.

Leccese, Mario. 2022. "Asymmetric Taxation, Pass-through and Market Competition: Evidence from Ride-sharing and Taxis." *EC '22,* 371–372. New York, NY, USA:Association for Computing Machinery.

Leccese, Mario. 2024. "Taxing ride-sharing: Which neighborhoods pay more?" *Journal of Re-*

gional Science, 64(4): 1393–1413.

Li, Hui, and Kannan Srinivasan. 2019. "Competitive Dynamics in the Sharing Economy: An Analysis in the Context of Airbnb and Hotels." *Marketing Science*, 38(3): 365–391. Publisher: INFORMS.

Li, Ziru, Chen Liang, Yili Hong, and Zhongju Zhang. 2022. "How Do On-demand Ridesharing Services Affect Traffic Congestion? The Moderating Role of Urban Compactness." *Production and Operations Management*, 31(1): 239–258.

Lomax, Timothy J. 1997. *Quantifying congestion.* Vol. 398, Transportation Research Board.

Mangrum, Daniel, and A. Molnar. 2017. "The marginal congestion of a taxi in New York City."

Miklós-Thal, Jeanine, and Greg Shaffer. 2021. "Pass-Through as an Economic Tool: On Exogenous Competition, Social Incidence, and Price Discrimination." *Journal of Political Economy*, 129(1): 323–335.

Poterba, James M. 1996. "Retail Price Reactions to Changes in State and Local Sales Taxes." *National Tax Journal*, 49(2): 165–176. Publisher: National Tax Association & National Tax Journal.

Seamans, Robert, and Feng Zhu. 2014. "Responses to Entry in Multi-Sided Markets: The Impact of Craigslist on Local Newspapers." *Management Science*, 60(2): 476–493.

Shapiro, Matthew H. 2018. "Density of demand and the benefit of Uber." *Research Collection School Of Economics*, 1–74.

Silva, JMC Santos, and Silvana Tenreyro. 2006. "The log of gravity." *The Review of Economics and statistics*, 641–658.

Stern, Nicholas. 1987. "The effects of taxation, price control and government contracts in oligopoly and monopolistic competition." *Journal of Public Economics*, 32(2): 133–158. Publisher: Elsevier.

Weyl, E. Glen, and Michal Fabinger. 2013. "Pass-Through as an Economic Tool: Principles of Incidence under Imperfect Competition." *Journal of Political Economy*, 121(3): 528–583. Publisher: The University of Chicago Press.

Wilking, Eleanor. 2020. "Why Does it Matter Who Remits? Evidence From a Natural Experiment Involving Airbnb and Hotel Taxes." Unpublished.

Zervas, Georgios, Davide Proserpio, and John W. Byers. 2017. "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry." *Journal of Marketing Research*, 54(5): 687–705.

ONLINE APPENDICES FOR "The Effects of Targeted Platform Taxes: Evidence from Ride-Sharing and Taxis"

Appendix A. Example with Linear Demand and Supply

Consider the same framework outlined in Section 2 and assume that $D(p) = a - bp$, $\sigma(L) = \sigma$ and $h(p) = zp$, with $a, b, z > 0$ and $a > bp$. Hence, the aggregate supply of rides is $S(p, L) = \sigma L z p$, where the number of drivers in the market L depends on the expected earnings and is endogenously determined in the model. The goal of this section is to show that under some conditions on the parameters of this linear model it is possible to have a pass-through rate above one, i.e., to have that the price received by drivers after the tax is higher than the pre-tax one.

Denote by L^0, p^0, Q^0, e^0 the pre-tax equilibrium number of drivers, the market price of a ride, the total number of rides and the drivers' individual earnings, respectively. Note that by definition $p^0 = p^0_{\mathrm{dr}}$. Suppose a tax t falling on riders is imposed on ride-sharing rides. I assume that $L^0 < N$, i.e., at the initial equilibrium not all the drivers are in the market, which requires that the earnings when all drivers are in the market are strictly below the highest outside option $\bar{\omega}$.[1] The tax induces a parallel shifts in demand and, by equating demand and supply, one can show that:

$$p'_{\mathrm{dr}}(L') = \frac{a - bt}{z\sigma L' + b} \tag{A.1}$$

$$Q'(L') = \frac{z\sigma L'(a - bt)}{z\sigma L' + b} \tag{A.2}$$

$$e'(L') = \frac{z\sigma(1-\nu)(a - bt)^2}{(z\sigma L' + b)^2}, \tag{A.3}$$

where Q', p'_{dr}, e' respectively are: the equilibrium number of rides, the price received by drivers and the individual earnings of drivers prevailing after the tax as a function of the new post-tax equilibrium number of drivers L'. The price paid by consumers is $p' = p'_{\mathrm{dr}} + t$.

[1] This assumption rules out the case in which all drivers choose to work after the tax, and hence the pass-through rate cannot exceed one because the equilibrium moves along the initial supply curve.

To fully characterize the equilibrium, one has to solve for L'. However, the final equilibrium in this model is the result of an adjustment process that proceeds as follows. First, demand for rides goes down, reducing the number of rides and the price earned by drivers, but increasing the price paid by riders. Second, this generates a reduction in expected earnings, which decreases the number of drivers in the market. The reduction in the number of drivers reduces the aggregate supply of rides, and hence leads to a further reduction in the number of rides and to an increase in the price earned by drivers. At this point, expected earnings change again, affecting the number of drivers in the market, and hence the aggregate supply of rides, which in turn prompts changes in price and number of rides. This feedback cycle repeats itself until the final equilibrium is reached, where the marginal driver deciding to enter earns exactly their outside option. Hence, in any equilibrium, it must hold that: $L' = \Pr(\omega \leq e')N$. Since drivers are heterogeneous in their outside options ω, which is uniformly distributed over $[0, \bar{\omega}]$ with $\bar{\omega} > 0$, the following equation pins down the fixed point of the system:

$$L' = \frac{Nz\sigma(1-\nu)(a-bt)^2}{\bar{\omega}(z\sigma L' + b)^2}. \tag{A.4}$$

Thus, once one has solved (A.4) for L', it is possible to find all the other equilibrium objects by using Equations (A.1)–(A.3).

I start by showing that, under the assumptions of this model, a solution to (A.4) always exists and it is unique.

Lemma 1. Suppose $L^0 < N$. Then, the solution to Equation (A.4), $L' \in [0, N]$, always exists and is unique.

Proof. Define μ' as the share of drivers in the market at the after-tax equilibrium, with $\mu' \in [0, 1]$. Then, one can rewrite Equation (A.4) as:

$$\mu' = \frac{z\sigma(1-\nu)(a-bt)^2}{\bar{\omega}(z\sigma\mu' N + b)^2}. \tag{A.5}$$

The LHS (RHS) is monotonically strictly increasing (decreasing) in μ'. Thus, L' exists if and only if the following two conditions are simultaneously satisfied:

$$\lim_{\mu' \to 0} \mu' \leq \lim_{\mu' \to 0} \frac{z\sigma(1-\nu)(a-bt)^2}{\bar{\omega}(z\sigma\mu' N + b)^2}, \tag{A.6}$$

$$\lim_{\mu' \to 1} \mu' \geq \lim_{\mu' \to 1} \frac{z\sigma(1-\nu)(a-bt)^2}{\bar{\omega}(z\sigma\mu' N + b)^2}. \tag{A.7}$$

(A.6) implies $\frac{z\sigma(1-\nu)(a-bt)^2}{\bar{\omega}(z\sigma N+b)^2} \geq 0$, which is always satisfied as all the terms on the LHS are strictly positive. (A.7) implies $\frac{z\sigma(1-\nu)(a-bt)^2}{\bar{\omega}(z\sigma N+b)^2} \leq 1$, which is always satisfied. To see this, note that the expression can be rearranged as:

$$\bar{\omega} \geq \frac{z\sigma(1-\nu)(a-bt)^2}{(z\sigma N + b)^2}$$

where the RHS represents the expected earnings of a driver when all N drivers are on the market and the LHS is the highest outside option. Since by assumption $L^0 < N$, it must be that the earnings when all drivers are in the market are strictly below the highest outside option, and hence holds (A.7).

Moreover, since both (A.6) and (A.7) are satisfied with strict inequality, then the solution to (A.4) is unique.

□

Next, I show that if a solution to (A.4) exists, then L' is decreasing in the tax, and hence $L' < L^0$.

Lemma 2. For any $t_1 < t_2$, $L'(t_1) > L'(t_2)$.

Proof. Suppose by contradiction $t_1 < t_2$ and $L'(t_1) < L'(t_2)$. Then,

$$L'(t_1) < L'(t_2) \implies \frac{a - bt_1}{a - bt_2} < \frac{z\sigma L'(t_1) + b}{z\sigma L'(t_2) + b},$$

but

$$\frac{a - bt_1}{a - bt_2} > 1 > \frac{z\sigma L'(t_1) + b}{z\sigma L'(t_2) + b},$$

a contradiction.

□

The next result shows under what conditions $p'_{dr} > p^0$.

Proposition 1. For any $t_1 < t_2$, $p'_{dr}(t_2) > p'_{dr}(t_1)$ if and only if

$$\frac{a - bt_2}{a - bt_1} > \frac{z\sigma L'(t_2) + b}{z\sigma L'(t_1) + b}. \tag{A.8}$$

In particular, when $t_1 = 0$ and $t_2 \equiv t$, then $p'_{dr} > p^0$ if and only if

$$L^0 - L' > \frac{bt(z\sigma L^0 + b)}{az\sigma}, \tag{A.9}$$

i.e., if and only if the change in the number of drivers on the market is large enough.

Proof. The results directly follow from evaluating Equation (A.1) at t_1 and t_2 (and at 0 and t, respectively), and rearranging the expressions.

□

Using a similar approach, one can also derive the following condition ensuring that the equilibrium number of rides decreases:

$$Q'(t_2) > Q'(t_1) \iff \frac{a - bt_2}{a - bt_1} < \frac{L'(t_1)}{L'(t_2)} \frac{(z\sigma L'(t_2) + b)}{(z\sigma L'(t_1) + b)}.$$

TABLE A.1. Example of the Equilibrium Effects of a \$1 Tax ($t = 1$) on Ride-sharing

(1) Parameters	(2) Pre-tax Equilibrium	(3) Shift in Demand (Off-Equilibrium)	(4) Post-tax Equilibrium
$a = 150$	$L_A = 90$	$L_B = 90$	$L_C = 50.76$
$b = 10$	$p_{A,\text{dr}} = 4.62$	$p_{B,\text{dr}} = 4.31$	$p_{C,\text{dr}} = 6.17$
$N = 100$	$p_A = 4.62$	$p_B = 5.31$	$p_C = 7.17$
$\bar{\omega} = 15$	$Q_A = 103.85$	$Q_B = 96.98$	$Q_C = 78.30$
$\sigma = z = 0.5$	$e_A = 4.26$	$e_B = 3.72$	$e_C = 7.61$
$\nu = 0.2$			

Notes: Column (1) summarizes the value of the model parameters chosen. Column (2) ((4)) characterizes the equilibrium before (after) the tax, i.e., at point A (C) in Figure 1A. Column (3) describes the values of the variables right after the shift in demand and before the first adjustment in the number of drivers L. This corresponds to point B in Figure 1A.

Example. Table A.1 presents an example with parameters chosen in a way that would lead to equilibrium adjustments consistent with those displayed in Figure 1A of Section 2. In particular, I choose parameter values such that, after a $1 tax, the change in the number of equilibrium drivers is large enough, i.e., satisfies (A.9). In this example, the pass-through rate of the tax is above one (2.55).

A.1. Different tax amounts on competing ride-sharing services

The previous section focuses on the role played by network effects between drivers and riders in inflating pass-through rates. However, Section 2 presents an additional mechanism that may lead to higher prices in the empirical context studied by this paper, namely the fact that ride-sharing companies offer two competing services (single and shared rides) and these are taxed asymmetrically.

Next, I discuss how the fact that ride-sharing platforms offer single and shared rides may impact the post-tax equilibrium. To gain intuition into the problem, consider a simple setting with any supply function for single and shared rides and with a demand for service $j = \{\text{single, shared}\}$ such as $D^j = a^j - b p^j + \zeta p^k$, with $j \neq k$ and $b > \zeta \geq 0$. This parametrization assumes similar own- and cross-price elasticities of demand for single and shared rides.[2]

Suppose a tax schedule is imposed with $t^{\text{single}} > t^{\text{shared}} > 0$. Under these assumptions, the tax schedule will always shift the demand for single rides inward. However, the tax could shift the demand for shared rides outward. This happens if and only if:

$$\frac{t^{\text{single}}}{t^{\text{shared}}} > \frac{b}{\zeta}. \tag{A.10}$$

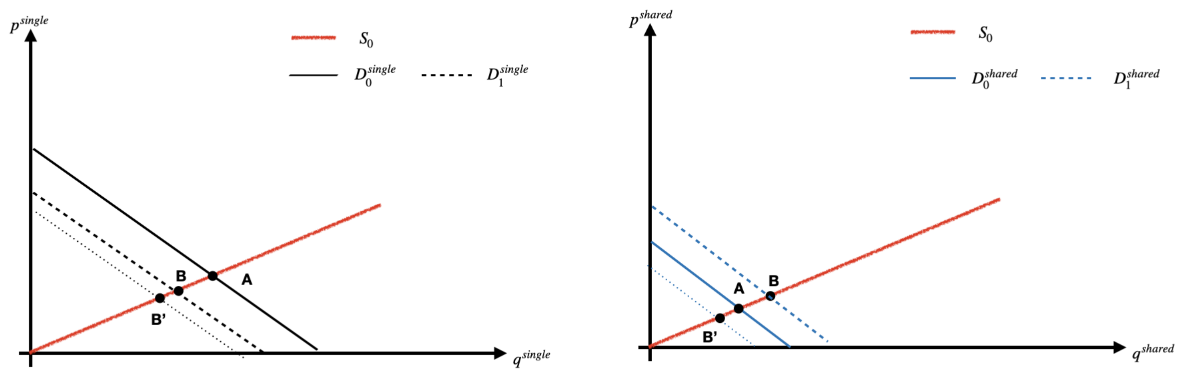
Panel A of Figure A.1 illustrates the effect of the tax on the market for single rides assuming no network effects between drivers and riders. Suppose that, before the tax, the equilibrium is at point A. The post-tax equilibrium is at point B, where drivers earn a lower price per ride and the number of rides is lower. While the sign of the shift in demand is not ambiguous, a lower cross-price elasticity of demand with shared rides would make the reduction in demand larger. For example, B' shows a post-tax equilibrium without network effects where $\zeta' < \zeta$. This implies that, in the market for single rides, a greater cross-price elasticity of demand between single and shared rides leads to higher prices and number of rides.

[2]It is also realistic to assume $a^{\text{single}} > a^{\text{shared}}$ because at the same price, the demand for single rides will be larger demand than that for shared rides.

Consider now the effects of the same tax on the market for shared rides. In this case, if the cross-price elasticity of demand ζ is sufficiently large, the tax policy could shift the demand for shared rides outward. Panel B of Figure A.1 presents this case: in the absence of network externalities, point B shows the new equilibrium when inequality A.10 holds, whereas B' illustrates the opposite case. Therefore, also in the market for shared rides, increasing the cross-price elasticity of demand between single and shared rides leads to higher prices and number of rides. However, the tax may also increase the number of shared rides relative to the initial equilibrium.

In practice, as discussed in Section 2, networks effects also play a role. Allowing for them, and hence for the supply to adjust in response to the tax, will increase the price and reduce the equilibrium number of rides in each market.

FIGURE A.1. Potential effects of the tax on the markets for single and shared rides



A. Single ride-sharing

B. Shared ride-sharing

Notes: The figures show the possible effects of a tax of ride-sharing which levies a larger amount on single than shared rides, assuming no network externalities between drivers and riders.

Appendix B. Robustness Checks

I begin by describing in detail the robustness checks I perform. Then, the next subsection presents the tables and figures with the results of the analyses.

B.1. Description of the Analyses and Discussion of Results

Equation 1 is the baseline specification I use to estimate the average short-run effect of the tax on the market outcomes of interest. To examine the dynamic effects of the tax—as shown in Figure 4 in the main text—I run event study regressions of the form:

$$\begin{aligned} y_{i,h,j,t} = &\beta_0 + \beta_1 \cdot Sample1920_{i,h,j} + \sum_{k \neq -1} \gamma_k \cdot \left(Sample1920_{i,h,j} \times D_{k,t} \right) + \\ &+ \beta_3 \cdot X_{i,h,j,t} + \alpha_i + \alpha_h + \alpha_t + \varepsilon_{i,h,j,t} \end{aligned} \tag{B.1}$$

where $D_{k,t}$ equals one if period t falls in the kth 5-periods interval (week) around period 0. I consider six weeks before and seven weeks after the tax, with their *corresponding weeks* in Sample 18-19, so that $k \in \{-6, ..., 6\}$. For example, $D_{1,t}$ equals one for all five days of the weeks starting on January 14, 2019 and on January 13, 2020. In this way, γs capture the average difference in the outcome variable between treatment and control group in each of the thirteen intervals around period 0. To control for each of the k intervals specific time-invariant characteristics, α_t includes their fixed effects. Moreover, since days of the week may have specific demand or supply patterns, I also include day-of-the-week fixed effects. Thus, $\alpha_t = \sum_{k \neq -1} \delta_{k,t} \cdot D_{k,t} + \sum_{u \in U} \xi_{u,t} \cdot I_{u,t}$, $U =$ {Monday, Tuesday, Wednesday, Thursday} where I_{uij} equals one when the observation refers to the uth day of the week. The remaining variables are defined as in Equation 1, and standard errors are two-way clustered by date and route.

Figure B.1 in this Appendix, and Figure 4 in the text show the results of these analyses for prices and number of rides. Post-treatment, the patterns are, in some cases, noisy, likely reflecting idiosyncratic daily shocks. While there are some minor departures from exact parallel trends, the pre-treatment trajectories are broadly stable, supporting the validity of the parallel trends assumption.

As mentioned in the text, I conduct three additional sets of robustness checks. The first one concerns the sample selection procedure described in Section 4. Since my empirical strategy hinges on using Sample 18-19 as a control group for Sample 19-20, which includes the actual tax implementation date, making them *comparable* is a necessary step. To that end, I exclude the following holiday periods: (i) the weeks including Thanksgiving 2018 and 2019; (ii) the week following Thanksgiving 2018 and the one preceding Thanksgiving 2019; (iii) Christmas 2018 and 2019. Points (i)-(ii) address the fact that Thanksgiving happened in different weeks of November in the two subsamples. Therefore, if I did not exclude all these weeks, I would eventually be lining up and comparing weeks in which a major holiday such as Thanksgiving took place with ones in which no holiday occurred. Point (iii) addresses the potential concern that riding patterns may differ across subsamples in a particular holiday week such as that of Christmas.[3] Table B.2 shows that although including these weeks in the final sample may lead to the parallel-trend assumption not holding in every pre-tax period, the estimates of the average effect of the tax on prices remain similar.

Furthermore, I perform additional robustness tests to validate the estimates of the effects of the tax on the number of the different types of pickups considered. To that end, first, since the week of New Year's Eve is aligned across Sample 18-19 and 19-20 and is not characterized by unusual riding pattern, I include it in my main sample. Nonetheless, I verify the robustness of my results to this choice by analyzing how results would change if I dropped the week of New Year's Eve from Sample 18-19 and 19-20. Table B.3 shows that the average effect on the number of pickups is similar to that in Table 4.

Second, the baseline specification presented in Equation 1 is a standard Two-Way Fixed Effects (TWFE) Difference-in-Differences (DiD) approach. Recently, several articles showed that the coefficients estimated in this way may not represent a straightforward weighted average of unit-level treatment effects when treatment effects are allowed to be heterogeneous (Roth et al. 2023). Specifically, when the treatment effect is heterogeneous, TWFE models may compare units that have already been treated, possibly leading to TWFE coefficients having the opposite sign of all individual-level treatment effects (an issue often referred to as "negative-weighting"). Borusyak, Jaravel and Spiess (2021) (henceforth, BJS (2021)) develop an imputation estimator that addresses the limitation of TWFE models. Generally speaking, negative-weighting concerns tend to be restricted to settings in which the treatment is staggered, i.e. units become treated at different points in time. However, although I compared units across different years (Sample 18-19 and Sample 19-20), in my context the treatment is not staggered because the tax is implemented for all TNP services on the same date. In effect, re-estimating my DiD specification following the approach in BJS (2021) yields similar results.

[3] For example, there could be special aspects of a Christmas week in a given year, such as the number of tourists using ride-sharing or taxis, that I would be otherwise unable to control for.

The third set of checks considers alternatives outcomes for prices and congestion. First, Panel A of Table B.4 shows that results are robust when I use the price per mile charged by ride-sharing companies instead of the price (in logs). Since changes in tipping behavior may mitigate riders' incentives to substitute away from single TNP rides, I also study how the tax affected tips for different rides. While tips are typically given as a percentage of the ride fare, and hence one may expect them to increase after the policy, Panel B of Table B.4 shows that tips did not change for downtown rides and decreased for non-downtown rides. However, the modest magnitude of these effects suggests that this mechanism is unlikely to contribute to explaining riders' substitution patterns. Second, the paper uses two different measures of congestion: speed, which is perhaps the most common proxy, and delay rate. For the latter, to measure the acceptable (i.e., the free-flow) travel rate (TR), previous studies have typically examined the variable's distribution during off-peak times. In the main text, I selected the 15^{th} percentile. To mitigate potential concerns regarding this choice, in Table B.5, I include several robustness checks using alternative definitions of acceptable travel rates. Specifically, I employ different percentiles of the distribution and standardized measures of acceptable TR for various city areas (e.g., central business district, suburban areas, etc.). All results are consistent with those presented in the main text.

Finally, Figure 3 highlights how ride-sharing prices (and hence potentially demand) may be non-stationary over the study period. Therefore, I further validate my approach by augmenting Equation 1 with a linear trend representing calendar weeks. Table B.1 shows that the estimation results for the effect of the tax on the price of different TNP services are robust to those shown in Table 3 in the main text.

COVID-19. In the main text, I discuss potential contamination from the COVID-19 pandemic. Here, I present several factors and supporting evidence showing that excluding observations after February 21, 2020, helps mitigate concerns about sample contamination.

First, the lockdown occurred after my sample period ended. Until mid-March, offices and universities remained open, and all events continued in person as usual. Specifically, Illinois issued its first "stay-at-home" order on March 20, 2020, and the University of Chicago halted in-person instruction only on March 15, 2020.

However, even without an official lockdown, individuals may have changed their behavior due to the spread of the virus or the news circulating about it. To assess this, I examined case numbers and found that they only began to increase in March 2020. As of March 2, 2020—already beyond my sample period—only four COVID-19 cases were confirmed by Illinois health officials.[4] While case numbers may be influenced by reporting biases, this is consistent with the notion that public attention and concern about COVID-19 were not particularly high before March 2020.

Additionally, economic activity in February 2020 did not show signs of slowing. The Chicago Business Activity Index (CBAI), developed by The Regional Economics Applications Laboratory at the University of Illinois at Urbana-Champaign, provides monthly estimates of changes in Chicago's economic activity. The CBAI report released on April 18, 2020, shows that economic activity grew in Chicago in February 2020, with the index increasing to 103.3 from 101.9 in January 2020.[5] This report further indicates that COVID-19 began impacting the economy only in March 2020.

Lastly, using Google search data, I analyzed whether there was significant interest in the term "COVID" during my sample period. Figure B.2 shows that interest in the term only began to rise in the first week of March 2020, spiking considerably by mid-March. While these patterns cannot completely dismiss the possibility that the anticipation of COVID-19's spread influenced some drivers' and riders' behaviors, they indicate that any such influence was limited and unlikely to significantly impact the results of my analyses.

[4] For example, see the article at: https://abc7chicago.com/coronavirus-chicago-illinois-update-cases-covid-19-news/5973196/.

[5] This report is available at: https://real.web.illinois.edu/wp-content/uploads/CBAI/20/CBAI_0420.pdf.

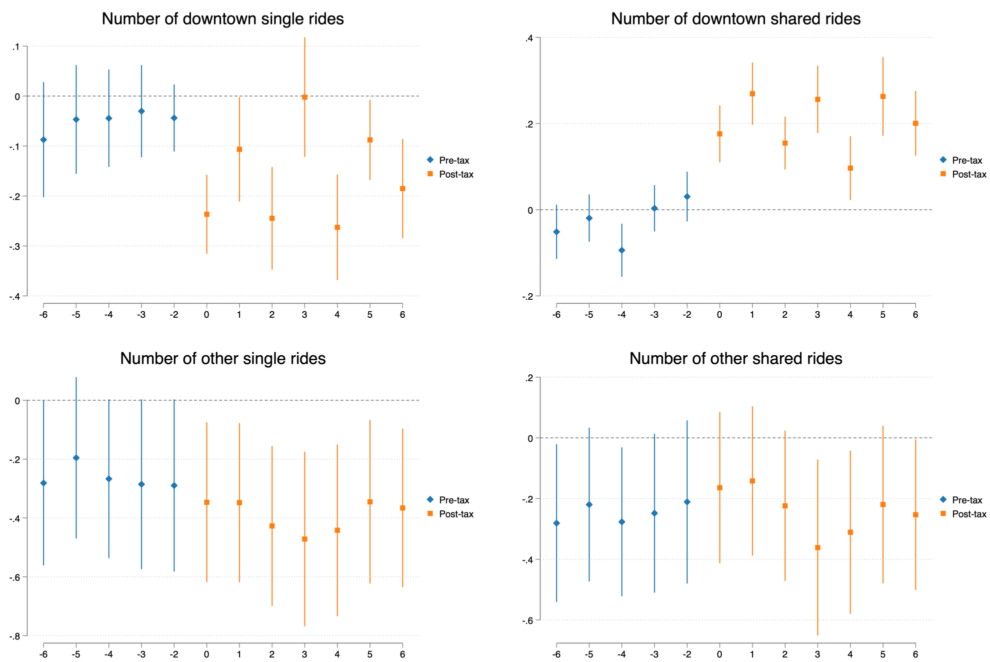
B.2. Results: Tables and Figures

TABLE B.1. The effect of the tax on TNP prices: Time trend robustness check

	(1) Single downtown	(2) Single other	(3) Shared downtown	(4) Shared other
Sample1920	-0.047***	0.004	-0.023	0.026***
	(0.014)	(0.005)	(0.029)	(0.007)
Sample1920 $\times$ Post	0.117***	0.033***	0.055***	0.018***
	(0.006)	(0.003)	(0.009)	(0.005)
Observations	127,700	1,581,150	107,321	1,229,076
Adj. R-sq	0.910	0.908	0.731	0.715
Route FE	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓
Period FE	✓	✓	✓	✓
Week of the year trend	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column describes the effect of the tax on the price (in logs) of different types of TNP rides. All regressions include controls for weather and the distance of the trip (in miles, as well as calendar week linear trend. Standard errors are two-way clustered at the route-date level and reported in parentheses.

FIGURE B.1. Event study for the effect of the tax on TNP pickups



Notes: Each figure plots the γ_ks coefficients and their 95% confidence intervals estimated via PPML regressions similar to Equation B.1. The coefficients summarize the dynamic impact of the tax on the number of different types of TNP rides. The x-axis displays the number of weeks since the implementation of the tax for observations belonging to *Sample 19-20*, or since January 7, 2019 for all the other observations. All regressions include controls for weather.

FIGURE B.2. Interest towards COVID-19 in the weeks following the tax implementation

Notes: The figures show the interest in searching the word "COVID" on Google Trends. The y-axis shows the relative search interest, for which a value of 100 is the peak popularity for the term, whereas a score of 0 means there was not enough search for this term. The top figure highlights the score during the week of February 16, the most recent included in my sample, whereas the bottom figure highlights the score during the first week of March.

TABLE B.2. The effect of the tax on TNP prices: no week dropped

	(1) Single downtown	(2) Single other	(3) Shared downtown	(4) Shared other
Sample1920	-0.044***	0.004	-0.024	0.026***
	(0.014)	(0.005)	(0.029)	(0.006)
Sample1920 $\times$ Post	0.115***	0.033***	0.055***	0.018***
	(0.007)	(0.004)	(0.008)	(0.004)
Observations	155,843	1,935,490	130,099	1,493,999
Adj. R-sq	0.907	0.907	0.728	0.716
Route FE	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓
Period FE	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column describes the effect of the tax on the price (in logs) of different types of TNP rides. The sample used retains all weeks, including Christmas and the weeks around Thanksgiving, as described in Section B. Moreover, all regressions include controls for weather and the distance of the trip (in miles). Standard errors are two-way clustered at the route-date level and reported in parentheses.

TABLE B.3. The effect on prices and number of pickups excluding NYE

	TNP				Taxi	
	(1) Single downtown	(2) Single other	(3) Shared downtown	(4) Shared other	(5) Downtown	(6) Other
Panel A: Prices (in logs)						
Sample1920	-0.049***	0.005	-0.027	0.030***	-0.242***	-0.022
	(0.015)	(0.006)	(0.031)	(0.007)	(0.069)	(0.033)
Sample1920 × Post	0.123***	0.036***	0.062***	0.022***	-0.005	0.008**
	(0.007)	(0.003)	(0.009)	(0.005)	(0.005)	(0.004)
Observations	118,609	1,471,993	99,873	1,143,758	56,069	240,442
Adj. R-sq	0.912	0.904	0.730	0.698	0.730	0.754
Panel B: Number of rides (PPML)						
Sample1920	0.359*	0.260***	-0.539***	-0.577***	1.457	-0.049
	(0.206)	(0.072)	(0.166)	(0.057)	(1.225)	(0.194)
Sample1920 × Post	-0.129***	-0.145***	0.217***	-0.003	0.032	-0.035
	(0.006)	(0.007)	(0.026)	(0.015)	(0.044)	(0.025)
Observations	147,840	5,209,920	147,840	5,114,880	147,840	4,427,520
Route FE	✓	✓	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns (1) to (4) describe the effect of the tax on the prices and number (in logs and levels) of different types of TNP rides, whereas the last two columns refer to the same effects for taxi rides. All regressions include controls for weather. Standard errors are two-way clustered at the route-date level and reported in parentheses.

TABLE B.4. The effect on tips and price per mile for TNPs

	(1) Single downtown	(2) Single other	(3) Shared downtown	(4) Shared other
Panel A: Price per mile				
Sample1920	0.366*	-0.019	0.166	0.038
	(0.213)	(0.048)	(0.110)	(0.052)
Sample1920 $\times$ Post	0.342***	0.115***	0.059***	0.039**
	(0.034)	(0.013)	(0.013)	(0.015)
Observations	127,697	1,580,999	107,318	1,228,861
Adj. R-sq	0.759	0.497	0.589	0.320
Panel B: Tips				
Sample1920	-0.003	0.006	0.014	0.014***
	(0.049)	(0.007)	(0.028)	(0.003)
Sample1920 $\times$ Post	-0.005	-0.018***	0.003	-0.005**
	(0.007)	(0.004)	(0.005)	(0.002)
Observations	127,700	1,581,150	107,321	1,229,076
Adj. R-sq	0.141	0.166	0.096	0.057
Route FE	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓
Period FE	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns (1) to (4) describe the effect of the tax on the prices per mile and tips for different types of TNP rides. All regressions include controls for weather and the distance of the trip (in miles). Standard errors are two-way clustered at the route-date and reported in parentheses.

TABLE B.5. The effect of the tax on alternative measures of the delay rate

	(1) Downtown-Downtown	(2) Downtown-Border	(3) Downtown-Other	(4) Border-Border	(5) Border-Other	(6) Other
Dep. Var. : DR_5						
Sample1920	3.218***	1.397***	0.202**	0.602***	0.088**	0.115***
	(0.128)	(0.074)	(0.099)	(0.062)	(0.039)	(0.024)
Sample1920 × Post	-0.504***	-0.232**	-0.060*	-0.166*	-0.058	-0.062**
	(0.173)	(0.109)	(0.034)	(0.083)	(0.036)	(0.026)
Adj. R-sq	0.616	0.547	0.499	0.406	0.464	0.237
Dep. Var. : DR_{25}						
Sample1920	1.059***	0.424***	0.202**	-0.252***	0.088**	0.115***
	(0.093)	(0.053)	(0.099)	(0.043)	(0.039)	(0.024)
Sample1920 × Post	-0.254*	-0.071	-0.060*	0.093	-0.058	-0.062**
	(0.134)	(0.076)	(0.034)	(0.070)	(0.036)	(0.026)
Adj. R-sq	0.275	0.444	0.499	0.414	0.464	0.237
Dep. Var. : DR_L						
Sample1920	3.462***	0.507***	0.002	-0.304***	-0.160***	-0.188***
	(0.050)	(0.033)	(0.116)	(0.030)	(0.053)	(0.036)
Sample1920 × Post	-0.505***	-0.129**	-0.080**	-0.126**	-0.092**	-0.107***
	(0.069)	(0.056)	(0.035)	(0.054)	(0.036)	(0.028)
Adj. R-sq	0.655	0.533	0.652	0.530	0.588	0.424
Observations	4,111	8,189	224,664	12,451	441,355	2,809,393
Route FE		✓	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column summarizes the results of a specification relative to one of the six segments considered. Each panel uses alternative measures of the delay rate. In the top and middle panels, I compute the acceptable travel rate using the 5^{th} and 25^{th} of the *TR* during off-peak times, respectively. In the bottom panel, I use the benchmark acceptable travel rates provided in Lomax et al. (1997) for different areas of a city (CBDs, major activity centers, and suburban areas). The Route FE is absent in Column (1) as there is only one route in the DD segment.

Appendix C. Additional Tables and Figures

TABLE C.1. The effect of the tax on taxi prices

	(1) Downtown	(2) Downtown	(3) Other	(4) Other
Sample1920	-0.243***	-0.551***	-0.022	-0.033
	(0.070)	(0.096)	(0.033)	(0.062)
Sample1920 × Post	-0.003	-0.008	0.008**	0.003
	(0.005)	(0.005)	(0.004)	(0.004)
Observations	59,781	59,781	258,162	258,162
Adjusted R-sq	0.734	0.665	0.754	0.646
Trip distance (miles)		✓		✓
Route FE	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓
Period FE	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column describes the effect of the tax on the price (in logs) of different types of taxi rides. All regressions include controls for weather. Standard errors are two-way clustered at the route-date level and reported in parentheses.

TABLE C.2. The effect of the tax on TNP and taxi trip miles

	TNPs				Taxis	
	(1) Single downtown	(2) Single other	(3) Shared downtown	(4) Shared other	(5) Downtown	(6) Other
Sample1920	-0.176***	-0.014***	-0.064***	0.019***	-0.155***	-0.003***
	(0.001)	(0.000)	(0.002)	(0.000)	(0.004)	(0.000)
Sample1920 × Post	-0.004***	0.002***	-0.002	-0.006***	-0.008**	-0.000
	(0.001)	(0.000)	(0.002)	(0.001)	(0.003)	(0.000)
Observations	160,160	5,650,320	160,160	5,549,440	160,160	4,811,040
Adj. R-sq	0.817	0.912	0.769	0.905	0.646	0.943
Route FE	✓	✓	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column describes the effect of the tax on the miles (in logs) of different types of TNP and taxi rides. All regressions include controls for weather.

TABLE C.3. The effect of the tax on congestion during rush hours

	(1) Downtown-Downtown	(2) Downtown-Border	(3) Downtown-Other	(4) Border-Border	(5) Border-Other	(6) Other
Dep. Var. : Average speed (logs, mph)						
Sample1920	-0.753***	-0.172***	0.009	0.024***	0.053***	0.063***
	(0.008)	(0.007)	(0.037)	(0.007)	(0.018)	(0.011)
Sample1920 × Post	0.088***	0.032***	0.021*	0.033***	0.022*	0.025***
	(0.012)	(0.010)	(0.011)	(0.011)	(0.012)	(0.008)
Sample1920 × Post × Rush-hours	-0.030	0.019	0.005	0.029	0.013	0.012
	(0.038)	(0.027)	(0.039)	(0.029)	(0.039)	(0.024)
Observations	4,111	8,189	224,670	12,451	441,364	2,810,250
Adj. R-sq	0.705	0.531	0.596	0.506	0.570	0.436
Dep. Var. : DR*						
Sample1920	1.724***	0.788***	0.009	0.079	0.053***	-0.027
	(0.126)	(0.050)	(0.037)	(0.047)	(0.018)	(0.021)
Sample1920 × Post	-0.557***	-0.036	0.021*	0.024	0.022*	-0.024
	(0.164)	(0.081)	(0.011)	(0.076)	(0.012)	(0.028)
Sample1920 × Post × Rush-hours	0.287	-0.170	0.005	-0.232	0.013	-0.096
	(0.175)	(0.148)	(0.039)	(0.152)	(0.039)	(0.102)
Observations	4,111	8,189	224,670	12,451	441,364	2,809,393
Adj. R-sq	0.373	0.484	0.596	0.407	0.570	0.194
Route FE		✓	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

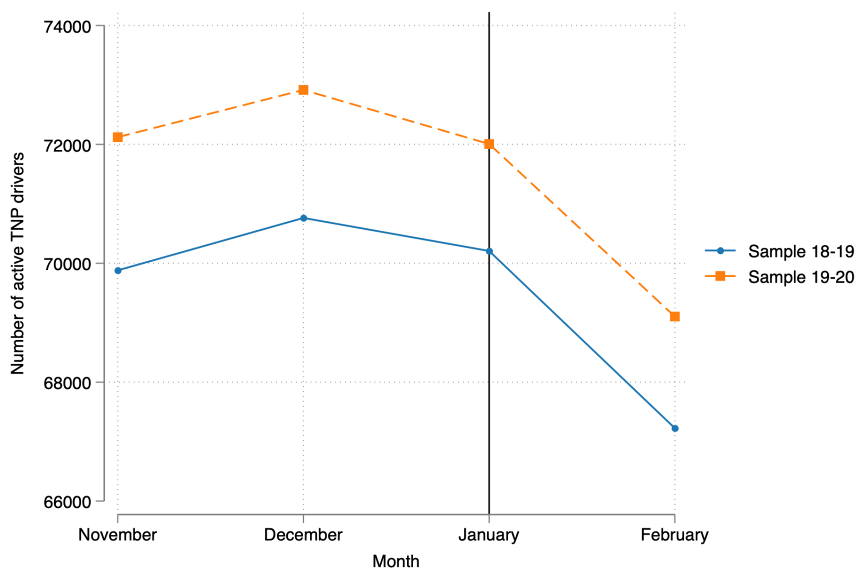
Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column summarizes the results of a specification relative to one of the six segments considered. In the top panel the dependent variable is the logarithm of the average speed (in mph), whereas in the bottom panel the dependent variable is the Delay rate. Rush-hour is a dummy equal to one when the observation is relative to a time between 7 am and 9 am or 4 pm and 6pm. In all regressions I control for (Sample 19-20 × Rush-hours) and (Post × Rush-hours), as well as for weather. The Route FE is absent in Column (1) as there is only one route in the DD segment.

TABLE C.4. Structure of the tax during off-peak times

Type of ride	Tax amount before January 6, 2020	Tax amount after January 6, 2020	Tax increment
Downtown Single TNP trip	$0.72	$1.25	+$0.53
Other Single TNP trip	$0.72	$1.25	+$0.53
Downtown Shared TNP trip	$0.72	$0.65	-$0.07
Other Shared TNP trip	$0.72	$0.65	-$0.07
Taxi trip	$0.00	$0.00	$0.00

Notes: The amounts refer to the tax paid by the provider to the City of Chicago for each trip completed off-peak. Peak times are Mondays, Tuesdays, Wednesdays, Thursdays, and Fridays between 6 am and 10 pm, whereas all the other times are defined as off-peak.

FIGURE C.1. Number of active TNP drivers over the months in each sample



Notes: Active drivers are those who complete at least one trip in a month. The black solid line at January identifies the month in which the policy began.

Appendix D. Analysis of the Tax's Impact on Border Trips and Additional Tables and Figures

TABLE D.1. Summary statistics of border trips

	Sample 18-19, pre 01/07			Sample 18-19, post 01/07			Sample 19-20, pre 01/06			Sample 19-20, post 01/06		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	N	mean	sd	N	mean	sd	N	mean	sd	N	mean	sd
Panel A: Border Single TNP												
Number of pickups	36,297	32.75	96.56	81,314	30.02	88.28	39,503	37.04	108.3	87,312	32.38	94.46
Trip miles	36,297	8.762	4.103	81,314	8.792	4.141	39,503	9.057	4.172	87,312	9.027	4.156
Trip price ($)	36,297	19.44	6.804	81,314	19.16	6.742	39,503	19.22	6.437	87,312	20.45	6.418
Trip minutes	36,297	25.94	10.82	81,314	24.75	10.38	39,503	26.38	10.89	87,312	24.33	9.891
Trip speed (mph)	36,297	20.43	6.696	81,314	21.48	7.037	39,503	20.87	6.953	87,312	22.39	7.205
Panel B: Border Shared TNP												
Number of pickups	34,475	11.66	25.54	77,621	10.87	23.42	30,197	6.075	10.98	69,045	6.732	13.02
Trip miles	34,475	9.059	4.213	77,621	9.269	4.287	30,197	10.53	5.153	69,045	10.57	4.893
Trip price ($)	34,475	12.08	5.387	77,621	12.11	5.245	30,197	13.04	5.068	69,045	13.56	5.199
Trip minutes	34,475	31.28	12.69	77,621	30.39	12.41	30,197	30.40	12.96	69,045	28.16	11.91
Trip speed (mph)	34,475	17.51	5.564	77,621	18.47	5.888	30,197	21.63	9.327	69,045	23.47	9.312
Panel C: Border Taxi												
Number of pickups	16,119	22.13	66.99	34,634	17.42	52.43	17,406	17.58	53.15	38,142	13.96	43.08
Trip miles	16,119	6.278	4.518	34,634	6.263	4.576	17,406	6.404	4.718	38,142	6.213	4.709
Trip price ($)	16,119	23.06	65.51	34,634	22.86	65.73	17,406	24.90	88.08	38,142	23.51	72.89
Trip minutes	16,119	22.54	12.18	34,634	21.65	11.70	17,406	24.20	12.61	38,142	22.60	11.69
Trip speed (mph)	16,066	16.55	8.685	34,527	17.17	9.914	17,384	15.93	9.097	38,106	16.49	9.675

Notes: The table presents summary statistics relative to different types of border trips for each route-hour in which at least a trip occurred in Sample 18-19 or Sample 19-20.

TABLE D.2. The effect of the tax for border trips

	TNPs				Taxis	
	(1) Single price	(2) Shared price	(3) # Single rides	(4) # Shared rides	(5) Price	(6) # Rides
Sample1920	-0.033***	0.018	0.322***	-0.595***	-0.080	0.0388
	(0.006)	(0.014)	(0.081)	(0.088)	(0.049)	(0.759)
Sample1920 × Post	0.100***	0.044***	-0.128***	0.180***	0.005	0.048
	(0.005)	(0.008)	(0.024)	(0.026)	(0.003)	(0.032)
Observations	244,426	211,338	314,080	314,080	106,294	314,080
Adj. R-sq	0.912	0.735	.	.	0.695	.
Route FE	✓	✓	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Each column describes the effect of the tax on the prices and number (both in logs) of different types of TNP and taxi rides. All regressions include controls for the weather (in miles) and regressions with price as a dependent variable also control for the distance of the trip (in miles).

References

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2021. "Revisiting event study designs: Robust and efficient estimation." *arXiv preprintarXiv:2108.12419*.

Lomax, Timothy J.. 1997. "Quantifying congestion." Vol. 398, Transportation Research Board.

Roth, Jonathan, Pedro H.C. Sant'Anna, Alyssa Bilinski, and John Poe. 2023. "What's trending in difference-in-differences? A synthesis of the recent econometrics literature." *Journal of Econometrics*.