Taxing Ride-sharing: Which Neighborhoods Pay More?*

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Abstract

I examine the short-run impact of taxing ride-sharing trips on the price and usage of ride-sharing across different community areas in Chicago and investigate whether the tax had unequal effects on community areas with different racial compositions. I document significant heterogeneity in price increases due to the tax across the community area of departure as well as across destination points, providing evidence that this was correlated with community areas' differential access to alternatives to ride-sharing, such as public transit. Clustering community areas based on their racial composition reveals that Black areas experienced particularly high price increases and percentage reductions in ride-sharing usage. Overall, the burden of the tax fell more heavily on minority-concentrated areas. These findings highlight the potential trade-offs between addressing negative externalities and exacerbating inequalities in urban policy, and suggest the need for further research on the impact of platforms' taxation on racial inequality.

Keywords: Heterogeneous pass-through, Racial disparities, Urban mobility, Ride-sharing.

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1 Introduction

In recent years, the rapid expansion of ride-sharing services has transformed the transportation landscape of many U.S. cities. While these companies have been lauded for improving service quality (Athey, Castillo and Chandar, 2021) and reducing matching inefficiencies (Fréchette, Lizzeri and Salz, 2019) compared to traditional taxis, they have also contributed to a surge in traffic congestion (Hang et al., 2019; Mangrum and Molnar, 2020; Li et al., 2021; Cairncross, Hall and Palsson, 2022), which is a significant and mounting problem that costs the average U.S. driver about $1,400 annually in terms of wasted fuel and time.[1] Hence, some recent congestion pricing schemes implemented by U.S. cities have taken the form of taxes on ride-sharing trips. However, the substantial heterogeneity in demand elasticities for ride-sharing across different neighborhoods can lead to higher price increases for trips starting in certain areas of the city, unequally affecting urban mobility capabilities of residents of different areas.

The close intersection between segregation and transportation has the potential to amplify the social impact of such heterogeneous effects of taxes on ride-sharing. In fact, housing and income segregation, which are still a distinguishing feature of American cities, not only limit integration, but also contribute to the disconnect between workers and jobs, possibly affecting the transportation costs, levels of employment, wages, and hence overall quality of life of low-income individuals and minority communities.[2] In this context, urban mobility plays a crucial role in undermining this mechanism because the ability to commute in an affordable and reliable way across neighborhoods can facilitate socio-economic and racial integration, and reduce spatial mismatches. Hence, taxing ride-sharing can exacerbate disparities across different groups of the population by unequally affecting urban mobility, thus generating unintended and undesirable social effects.[3]

[1] Estimates according to the INRIX 2017 Global Scorecard.

[2] Kain (1968) was the first to develop this spatial mismatch hypothesis arguing that the persistent residential segregation of minorities away from the areas in which job opportunities were concentrated reduced employment across minorities.

[3] Bailey et al. (2020) highlight the importance of transportation infrastructure in shaping urban social networks by showing that social connectedness—measured through connections between individuals

While there is a long literature on the distributional impact across income groups of taxes aiming to reduce congestion,[4] less attention has been devoted by policymakers and researchers to the potentially unequal consequences of similar taxes for different racial groups. The purpose of this paper is to examine the heterogeneous short-run effects of taxes on ride-sharing prices across neighborhoods, and then to investigate whether the tax unequally impacted areas in which different racial groups are concentrated, focusing on ride-sharing prices and commuting flows. I study the case of Chicago where in January 2020 the city increased the tax on ride-sharing from \$0.72 to \$3.00 for each ride starting or ending in the downtown area of the city and to \$1.25 for any other trip. This tax—the largest ever levied on ride-sharing in the US—provides the exogenous variation for my analyses. Moreover, the fact that Chicago is a segregated city, with the Black population concentrated in the south of the city, Hispanic in the west, and White population in the north,[5] makes it easier to identify racial areas within the city. Since racial segregation remains persistent in many US cities,[6] and similar taxes are either on the policy agenda or have already been implemented in other US cities,[7] the findings of this study are informative beyond the borders of Chicago.

My approach to studying the impact of the Chicago tax consists of two steps. First, I use a "Regression Discontinuity in Time" design that accounts for recurrent seasonal effects at the tax implementation date to estimate the differential impact of the tax on ride-sharing prices across Chicago neighborhoods. This design allows me to identify the short-run effects of the tax, i.e., around the cutoff date, excluding from the sample data potentially contaminated

on Facebook—declines faster in travel time and travel cost than it does in geographic distance and it is positively correlated with the number of taxi trips.

[4]See, for example, Foster and Richardson (1975), Arnott, De Palma and Lindsey (1993), Small (1983), Santos and Rojey (2004), Small et al. (2006), Schweitzer and Taylor (2008), Light (2009), Van Den Berg and Verhoef (2011), Hall (2018, 2021).

[5]"Hispanic" is usually considered as an ethnicity rather than a race. However, in the American Community Survey that I use, Asian, Black, Hispanic, and White are mutually exclusive groups, to which I refer as races.

[6]See for example: `https://www.brookings.edu/essay/trend-1-separate-and-unequal-neighborhoods-are-sustaining-racial-and-economic-injustice-in-the-us`.

[7]For example, Washington D.C. levies a tax on each ride-sharing trip amounting to 6% of the fare. Moreover, in February 2019, NYC imposed a surcharge for trips that begin in, end in, or pass through Manhattan south of and excluding 96th Street. In the same year, The Los Angeles County Metropolitan Transportation Authority was studying a possible tax on Uber and Lyft rides (see: `https://laist.com/news/uber-lyft-traffic-congestion-study`).

by the outbreak of COVID-19.[8] Second, I aggregate community areas into four larger areas (Asian, Black, Hispanic, White) based on the percentage of population of any race residing in each community area, and I use the same Regression Discontinuity in Time design to estimate changes in total number of trips and prices—which I then use to compute tax pass-through rates providing an estimate of the incidence of the tax across racial areas. I focus on trips starting from any of the four racial areas identified and I distinguish trips to Chicago downtown (more precisely, to "The Loop") and to employment subcenters (McMillen, 2001) from those to any other area of the city.

First, I find that the effect of the tax on prices varied significantly depending on the community area where the trip began and the destination point, and I show that this was correlated with community areas' differential access to alternatives to ride-sharing. In particular, trips starting in areas with limited access to public transit and—to a lower extent—private vehicles experienced a greater increase in prices due to the tax. Second, I show that rides starting in minority-concentrated community areas had higher price increases, especially in Black areas where price increments ranged from \$0.91 to \$2.44 pre-tax, per ride. By contrast, White areas had lower increases, ranging from \$0.72 to \$2.06 pre-tax, per ride. Third, the increased cost of ride-sharing resulting from the tax exclusively reduced the number of ride-sharing trips originating in Black and Hispanic areas. Lastly, based on simple back-of-the-envelope calculations, I show that the burden of the tax fell more heavily on areas with higher concentrations of minorities.

These analyses contribute to the urban economics and public finance literature examining the impact of congestion taxes on transportation prices and urban mobility by showing that taxes on ride-sharing primarily affect riders, with pass-through rates often exceeding 100%, particularly in areas with limited access to alternative transportation options, such as minority-concentrated neighborhoods. As a result, these taxes can lead to a reduction in ride-sharing usage, especially in areas where prices increase substantially. The paper

[8] A different design would be needed if one was interested in the long–run effects of the tax. Such analyses would however be difficult in my setting due to data limitation, and in particular due to the outbreak of COVID-19 in March 2020 (the most recent date I use in my estimation is February 19).

by Agrawal and Zhao (2023) is particularly relevant, as it numerically explores the impact of taxes on Uber, contrasting them with congestion taxes. This study complements its conceptual framework by offering a reduced-form empirical analysis of the effects of taxing ride-sharing trips in Chicago.

Tax overshifting has also been observed in other empirical studies across different industries (Poterba, 1996; Besley and Rosen, 1999; Kenkel, 2005) and is often theoretically explained by the existence of market power (Delipalla and Keen, 1992; Hamilton, 1999; Anderson, Palma and Kreider, 2001; Hamilton, 2009; Weyl and Fabinger, 2013). However, it could also result from other aspects such as the degree of complementarity or substitutability with other products (Agrawal and Hoyt, 2019) or the presence of network effects (Belleflamme and Toulemonde, 2018).[9]

Furthermore, I document significant heterogeneity in shifting patterns across geographic locations, a finding that contributes to the literature on the spatial heterogeneity of tax pass-through rates (e.g., Harding, Leibtag and Lovenheim (2012) and Hindriks and Serse (2019)). While these articles focus on traditional consumption goods (cigarettes and alcohol, respectively), I study ride-sharing services. These platforms function as peer-to-peer marketplaces, connecting drivers to riders, thereby introducing the potential for taxes to yield non-standard effects (Kind, Koethenbuerger and Schjelderup, 2008).[10]

Finally, my findings can inform the policy discussions regarding the distributional consequences of policies aimed at correcting negative externalities, such as congestion. In Chicago, the tax penalized areas where the population from minorities is concentrated more than others, without significantly reducing congestion (Leccese, 2022). Although I specifically focus on taxes on ride-sharing trips, my results mainly rely on differential access across neighborhoods to alternatives to the taxed product. This means that the same mechanisms can apply

[9]Both these forces may be particularly relevant in the context of taxes on ride-sharing because each platform offers multiple competing services (e.g., single and pooled rides) and indirect network externalities between drivers and riders are present.

[10]Wilking (2020) another peer-to-peer marketplace finding that shifting the obligation to remit taxes from independent renters to Airbnb increases both prices and revenues, and reduces tax evasion, making the policy an effective tax increase.

to other similar settings. Moreover, while I examine the interaction of taxation with racial disparities, the correlation between race and income suggests that relations with income inequality issues are also possible.[11] This insight is consistent with the findings of other papers. For example, Donna (2021) shows that gasoline taxes are regressive since low-income consumers are more likely to switch from cars to public transit, whereas Almagro et al. (2024) show that road pricing can significantly reduce consumer surplus in the short-run, particularly for middle-income consumers, who are most reliant on cars.

The rest of the paper is organized as follows. Section 2 presents the background of the study, describing the details of the tax and discussing its relationship with congestion and housing segregation. Section 3 describes the data and Section 4 the empirical framework. Section 5 documents the heterogeneity in the increase in ride-sharing prices across trips with different endpoints. Section 6 analyzes the impact of the tax on racial areas, while a conclusion is offered in Section 7.

2 Background of the Tax: Traffic Congestion and Housing Segregation in Chicago

Ride-sharing has become a critical component of the transportation infrastructure in large urban areas, complementing and substituting for private vehicles and public transit (Hall, 2018; Stiglic et al., 2018; Erhardt et al., 2019; Djavadian, Farooq and Meshkani, 2021; Gonzalez-Navarro et al., 2022; Agrawal and Zhao, 2023). In Chicago, a report produced in 2019 by the Business Affairs and Consumer Protection (henceforth, the BACP Report) found that between 2015 and 2018, the annual number of trips provided by ride-sharing companies (also called "Transportation Network Providers", and henceforth TNPs) in Chicago grew by 271%.[12] According the BACP Report, this explosive growth is an important factor for the

[11]Figure B.2 in the Appendix shows that a larger percentage of the Black or Hispanic population in a community area, is correlated with a lower median income in that community area. Instead, the opposite holds for the percentage of the White population.

[12]The BACP Report is available at: `https://www.chicago.gov/content/dam/city/depts/bacp/Outreach\%20and\%20Education/MLL_10-18-19_PR-TNP_Congestion_Report.pdf`.

increase in traffic congestion.[13]

Therefore, with the main objective of reducing congestion, Chicago implemented a new tax starting January 6, 2020.[14] In effect, the policy was a tax on ride-sharing as no other transportation mean (public transit, private cars, or traditional taxis) was taxed. The tax replaced the previous flat tax of \$0.72 on every TNP trip with a tax schedule that levies different amounts based on the geographical endpoints and the time of the ride. In particular, the tax amounted to \$3.00 per-ride for trips between 6 AM and 10 PM starting or ending in a designated surcharge zone, which entirely includes the Central Business District of the city (i.e., The Loop), while for any other ride the tax amounted to \$1.25 per-ride.[15] The Chicago tax is the highest surcharge faced by TNPs in the US.

Furthermore, Chicago is one of the most racially segregated cities in the U.S., with the Black population living predominately on the south and west sides, Whites to the north, and Hispanics to the northwest and southwest.[16] In addition, the correlation between racial and economic segregation suggests that housing segregation may also increase in the future because the number of concentrated low-income community areas is on the rise (Breymaier, Davis and Fron, 2013). For example, in 2017, as compared to areas in which White population is predominant, in Black or Hispanic areas, residents were 20% less likely to own the house, and for owners, the median property values were almost \$100,000 lower.[17]

Hence, the size of the tax, combined with the fact that the city is highly segregated, makes Chicago an ideal setting to study the heterogeneous impact on different racial groups of policies targeting negative externalities.

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[13] The BACP Report argues that the influx of TNP trips during rush periods in the downtown area is a substantial factor in reducing bus speeds, although no direct causal relationship, nor correlation, with congestion is provided in the report.

[14] An additional goal of the tax was that of raising money for the city budget.

[15] In this paper, I focus on single rides. However, in practice, the tax was different for shared rides, amounting to \$1.25 for trips between 6 AM and 10 PM starting or ending in the designated surcharge zone and to \$0.65 for any other trip.

[16] This is shown by Acs et al. (2017) by developing a proxy for Black-White and Hispanic-White racial segregation. Their approach uses a spatial proximity index to measure how groups cluster into enclaves within a region.

[17] See the Institute for Research on Race and Public Policy report, "A Tale of Three Cities: The State of Racial Justice in Chicago Report," which is available at: `https://stateofracialjusticechicago.com`.

3 Data

In this section, I describe the data and summarize how I construct my final sample and the key variables used in my analyses.

3.1 Data Description

I use data from three different sources: the City of Chicago Data Portal (CCDP), the Chicago Metropolitan Agency for Planning (CMAP), and the National Weather Service Forecast Office (NWFSO).

The CCDP makes publicly available trip-level data on TNPs. Each observation includes the date, time, price, and endpoints of the ride, as well as other information including length (in miles), duration (in seconds), tip, and an identifier for whether the ride was shared (i.e., two or more riders booked separately and shared the ride) or not. However, the dataset does not specify the company which provided the ride. For geographical endpoints, 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 consider, which allows me to compare results over time. The city of Chicago started to collect this data in November 2018, and data are updated quarterly. Since 2013 the CCDP collects in a different dateset similar information for trips provided by traditional taxis. I use this dataset to construct additional control variables for my regression analyses.

The CMAP publishes community data snapshots, which summarize demographic, housing, employment, transportation, land use, revenue, and water data in northeastern Illinois. In my dataset, each observation is one of the 77 Chicago CAs—to which I will also refer as neighborhoods—and I mainly use information on demographics, income, number of cars available, preferred commuting means of transportation and education, all cut by race (Asian, Black, Hispanic, White). This dataset uses 5-year estimates from the 2014-2018 American Community Survey, as well as other information coming from multiple other sources, including the U.S. Census Bureau, Illinois Environmental Protection Agency, Illinois Department of Employment Security, Illinois Department of Revenue, and the CMAP. I supplement the information from this source by hand-collecting data on the number of Ltrain stations in each CA, which I use in my analysis of the possible drivers of the heterogeneity in the increase in prices.

Lastly, the NWSFO publishes data on weather in Chicago over time. Each observation is a day and information about the amount of precipitations, wind speed, snowfall, temperature and a dummy for whether there was thunder or not are provided.

3.2 Sample Construction

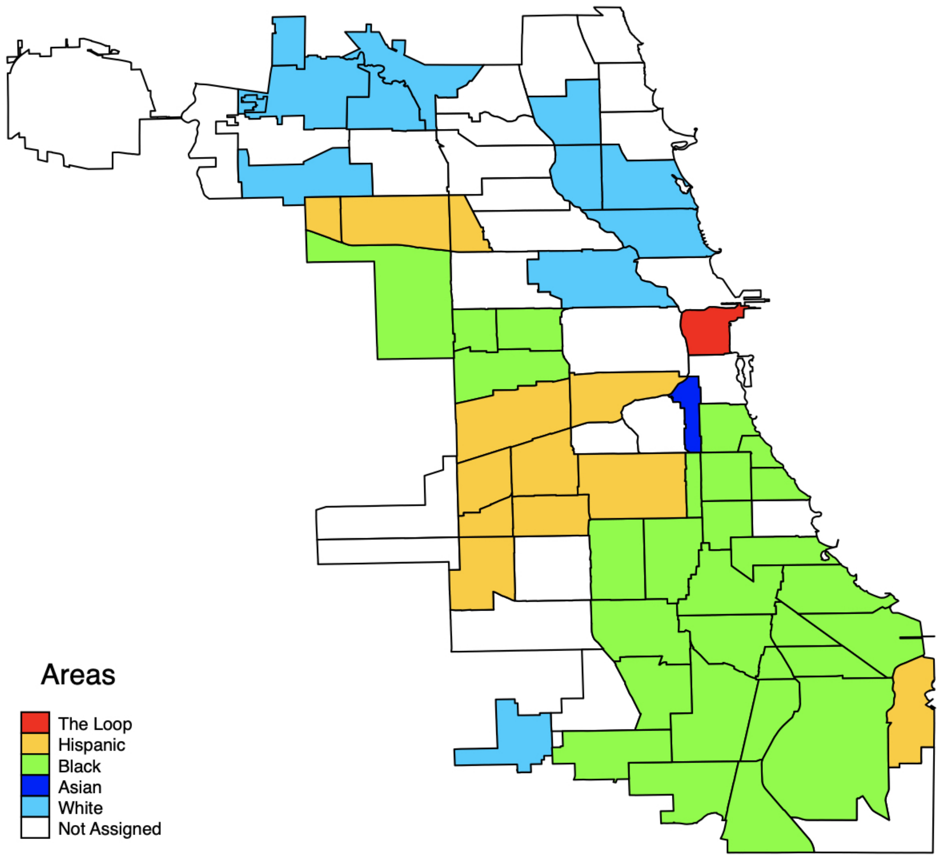
I restrict attention to single rides and merge TNP trip data to community data snapshots using community area numbers and to weather data using calendar dates. Given the schedule of the tax, I focus on week-day trips starting after 6 AM and ending before 10 PM, and I drop holidays from the sample.[18] Moreover, I drop trips with prices below \$1 or above \$200 as well as those with a distance longer than 100 miles: all together these account for about 0.2% of the observations.

I consider different types of rides based on geographical endpoints and time of the day, partly to account for the different tax amounts levied by the city. Concerning the starting point of rides, I start by separately considering trips from any CA. Then, using data on the percentage of Asian, Black, Hispanic, and White population residing in each CA, I cluster CAs into four larger racial areas (Asian, Black, Hispanic, or White). In particular, I assign each CA to a racial area (Asian, Black, Hispanic, or White) whenever there is a predominant race in the CA, which is defined to be the case when the percentage of the population of that race is equal to or above 60%.[19] This threshold ensures a clean identification of racial areas and avoids assigning a CA to a racial area when the second-largest racial group is close to the first. However, all results are robust to the use of both lower (e.g., above 50%) and

[18] I define the following days as holidays: Thanksgiving Day and the day after, Christmas' Eve, Christmas Day, New Year's Eve, New Year's Day, and December 5, 2018, which was a national day of mourning in honor of George H. W. Bush.

[19] Figures B.4, B.5, B.6, B.7 in the Appendix illustrate the distribution of population from each race across Chicago CAs.

Figure 1: Racial Areas in Chicago



Notes: The map of Chicago illustrates the Asian area (in blue), the Black area (in green), the Hispanic area (in yellow), the White area (in light blue) as well as the loop (in red). Any other area in which there is no predominant race is left in white.

higher thresholds. This approach assigns every CA to one of the four races or no race if there is no predominant race in the CA. Hence, in the set of analyses considering trips starting from any of the racial areas, I drop trips starting from "not assigned" CAs (i.e., those in white in Figure 1).[20]

One caveat needs to be considered. Although The Loop is predominantly White, I distinguish it from the other White CAs because it is part of the surcharge zone, and hence subject to a higher tax amount, and has a unique strategic importance in the city. In fact, in 2018 The Loop held 28.4% of all private-sector jobs in Chicago, and 9.4% of all jobs in

[20]As suggested by the summary statistics reported in Table 1, this operation implies focusing on roughly 20% of the total number of ride-sharing trips happening in Chicago.

the Metro Area, housing a large number of City, County, and State government workers.[21] Figure 1 illustrates all the CAs of Chicago, where CAs belonging to the Asian area are colored in blue, CAs belonging to the Black area are colored in green, CAs belonging the Hispanic area are colored in yellow, CAs belonging to the White area are colored in light blue, and The Loop is colored in red.

When it comes to trip destinations, I consider rides to employment subcenters and other CAs. Employment subcenters are defined by Mcmillen (2003) as areas with a concentration of firms large enough to significantly impact the distribution of population, employment, and land prices. In the data, these areas are identified as those offering more than 10,000 jobs (Giuliano and Small, 1991).[22] As shown by McMillen (2001), Chicago is not a monocentric city because firms are also concentrated outside of The Loop, which is the Central Business District. Although Chicago exhibits employment dispersion, The Loop is by far the largest employment subcenter with over 420,000 jobs. This implies that while economic activity is spread across the city, the Loop holds considerable influence, resulting in price gradients akin to those in a monocentric model. Therefore, I further distinguish trips to The Loop from those to other employment subcenters.

Additionally, in the analysis of Section 6, where I examine trips originating from various racial areas, I further categorize the trips according to their time of occurrence. Specifically, I classify trips that take place between 6 AM and 10 AM as "work-schedule" trips, as this time period is typically associated with commuting to work, while any other trip is referred to as a "leisure-schedule" trip. Overall, in Section 6, I define twenty-four distinct ride types based on the area of origin (Asian, Black, Hispanic, White), the destination area (The Loop, employment subcenters, or any other location), and the trip's time (work-schedule or leisure-schedule).

Lastly, my sample focuses on the period around the implementation of the tax, i.e., January 6, 2020. I consider different intervals of days around the cutoff date, the longest

[21]For more details, see the report "The State of The Loop" available at: `https://loopchicago.com/assets/244c02acb7/State-of-the-Chicago-Loop-2018-Economic-Profile.pdf`.

[22]Table A.1 lists all the CAs with more than 10,000 jobs.

Table 1: Average prices and number of rides for different types of trips before the tax

	Rides to the Loop		Rides to Employment Subcenters		Other Rides	
	Work-schedule	Leisure-schedule	Work-schedule	Leisure-schedule	Work-schedule	Leisure-schedule
Price from Asian Area	11.59	10.54	13.22	12.51	13.66	13.36
Price from Black Area	17.75	16.40	17.41	16.09	13.03	12.72
Price from Hispanic Area	15.39	14.92	14.43	13.65	13.15	13.35
Price from White Area	14.13	13.87	14.41	11.88	17.65	15.25
Price from Not Assigned Areas	12.66	13.17	16.44	15.39	19.89	21.64
Price/mi from Asian Area	3.47	3.85	4.24	3.84	3.87	4.37
Price/mi from Black Area	2.39	2.28	2.81	3.05	3.78	3.99
Price/mi from Hispanic Area	2.87	2.77	3.46	3.78	3.80	3.76
Price/mi from White Area	3.30	3.17	3.80	4.44	3.27	3.34
Price/mi from Not Assigned Areas	5.66	6.03	4.59	4.77	3.14	2.98
# of rides from Asian Area	927	3,527	3,037	13,557	1,152	5,052
# of rides from Black Area	16,560	17,511	68,610	114,542	88,501	226,459
# of rides from Hispanic Area	11,040	10,249	52,762	91,888	30,653	76,534
# of rides from White Area	76,079	63,394	281,451	739,222	32,843	127,834
# of rides from Not Assigned Areas	207,411	374,418	758,597	2,567,918	153,257	653,700

Notes: For each type of ride, I report the average price of a ride in \$ per ride, the average price per mile in \$ per mile and the natural logarithm of the absolute number of rides. The statistics refer to the 29 days week-days preceding the start of the tax, excluding holidays.

being 34 days, which implies that the most recent calendar date in the sample is February 20, 2020. In this way, I avoid any contamination following the outbreak of COVID-19.[23] To control for recurrent seasonality at the policy cutoff, I use a subsample of the same length around January 7, 2019, which is the same Monday in the year before the start of the tax. Hence, my final sample is constructed by pooling together two subsamples—which I will refer to as "Sample 18-19" and "Sample 19-20"—of at most 34 weekdays around January 7, 2019 and January 6, 2020, respectively. Table 1 provides summary statistics relative to the 29 week-days before the implementation date of the tax for the key outcome variables across the different types of rides considered.

4 Empirical Framework

My identification strategy exploits the exogenous variation that occurred due to the implementation of the tax on January 6, 2020, to compare TNP prices and pickups before and after this cutoff date. This is the main intuition behind the conventional Regression Discontinuity in Time (RDiT) design (e.g., Imbens and Lemieux (2008), Anderson (2014)), which is a regression discontinuity design that uses time as the running variable. However, a straightforward application of the RDiT design would lead to biased estimates in my context because ride-sharing prices are characterized by significant seasonal variations around the cutoff date. In effect, the tax began on the first Monday after a holiday period, during which activities usually slow down. For example, TNP prices tend to be lower at the end of the year compared to their level in January and February. Thus, to isolate the effect of the ride-sharing tax from recurring seasonal effects at the cutoff date, I adopt an approach similar to that developed in Klein, Salm and Upadhyay (2022).[24] The idea is to compare the changes in prices and pickups that happened around the date when the tax began with those that occurred after a hypothetical tax implementation date, which is defined as the

[23] A "stay at home" order was issued for the state of Illinois on March 20, 2020. UChicago stopped in person instruction on March 15, 2020.

[24] Klein, Salm and Upadhyay (2022) call their approach "Differences-in-Regression-Discontinuities" and use it to study patients' response to dynamic incentives in health insurance contracts with deductibles.

first Monday after the same period of holidays in the previous year, i.e., January 7, 2019.[25]

Effectively, I pool together two subsamples, one including 29 days on either side of the actual policy date (Sample 19-20), and the other of the same size centered around January 7, 2019 (Sample 18-19), and I estimate the following baseline equation for trip o occurring on day t:[26]

$$p_{ot} = \delta_0 + \boldsymbol{\delta_t} + \alpha \cdot \mathbb{1}\{D_t \geq 0\} + \beta \cdot \mathbb{1}\{D_t \geq 0\} \cdot Y20_t + \gamma_1 \cdot D_t +$$

$$+\gamma_2 \cdot D_t \cdot \mathbb{1}\{D_t \geq 0\} \cdot Y20_t + \gamma_3 \cdot D_t \cdot \mathbb{1}\{D_t \geq 0\} \cdot Y19_t + \boldsymbol{X_t'} \cdot \boldsymbol{\pi} + \varepsilon_{ot}, \qquad (1)$$

where p_{ot} is the price of trip o that occurred in day t starting in any CA and ending within the Loop, in an employment subcenter (excluding the Loop) or in any other CA; $Y20_t$ ($Y19_t$) is a dummy equal to 1 if the observation belongs to Sample 19-20 (18-19); D_t is normalized to be zero on January 7, 2019 and on January 6, 2020, and measures the number of days between the observation and January 7, 2019 or January 6, 2020, depending on the subsample the observation belongs to; $\mathbb{1}\{D_t \geq 0\}$ is a dummy variable which equals one on or after January 7, 2019, for observations in Sample 18-19 whereas it equals one on or after January 6, 2020 for observations in Sample 19-20. Thus, α controls for the seasonal change in prices around the cutoff date; $\boldsymbol{\delta_t}$ are seasonal fixed effects, which include dummies for days of the week, weeks of the year, and months: these account for other sources of seasonal variation that are constant across Sample 18-19 and Sample 19-20; $\boldsymbol{X_t}$ is a matrix of control variables which includes the length of the trip in miles, the amount of precipitations, wind speed, snowfall, temperature and a dummy for whether there was thunder. Hence, $(\mathbb{1}\{D_t \geq 0\} \cdot Y20_t)$ is equal to 1 on or after the beginning of the tax (January 6, 2020), and 0 otherwise, and β

[25] An alternative approach could be a two-step procedure that first seasonally adjusts the data using several years of observations, and then compares prices before and after the tax. However, this is not feasible in my setting because data on TNP trips are only available since November 2018.

[26] To make the two subsamples comparable, I construct them so that the number of times each day of the week (Monday-Friday) appears in the sample before the cutoff dates (i.e., January 7, 2019 for Sample 18-19, and January 6, 2020 for Sample 19-20) is the same across subsamples. The same trivially holds after the cutoff dates, since there are no holidays in either subsample. This process implies dropping a few dates that are not holidays. For example, I drop December 4, 2019, since on December 5, 2018 there was a non-recurrent holiday.

represents the coefficient of interest, capturing the effect of the tax net of seasonality.

I assume that the potentially endogenous relationship between the error and the date is eliminated by the polynomial $(\gamma_1 \cdot D_t + \gamma_2 \cdot D_t \cdot \mathbb{1}\{D_t \geq 0\} \cdot Y20_t + \gamma_3 \cdot D_t \cdot \mathbb{1}\{D_t \geq 0\} \cdot Y19_t)$, where the first term captures the average linear trend in p across both subsamples and the second (third) term captures the trend-deviation from the trend in 2020 (2019) after $D_t = 0$. I prefer this specification over more flexible functional forms, such as D_t fixed effects, because holidays fall on different weekdays in Sample 18-19 and Sample 19-20, and this makes it difficult to line up the two sets of dates perfectly across the two subsamples. This generalizes the local linear models used in the RDiT literature to account for the fact that I pool together two different subsamples, and allows for changes in the slope of the relationship not only after the actual cutoff date but also after the hypothetical one. Moreover, since the choice of the length of the subsamples that I pool together is arbitrary—I choose 29 days for the main specifications following examples in the RDiT literature (for example, Anderson (2014) chooses 28 days)—as conventional in the literature, I run several robustness checks using different bandwidths around the cutoff dates (between 24 and 34 days).

Three additional assumptions underlie this model. First, the potentially endogenous relationship between errors and time does not change discontinuously on or near the date on which the tax begins. Second, seasonality has on average the same effect across years. Third, the relation between the dependent variable and the date does not change across the two subsamples I pool together.

Finally, it is important to emphasize that the design proposed in this paper can only be used to identify the "local" (i.e., close to the cutoff date) effects of the tax. However, in practice, platforms and riders' responses may be gradual, implying that a longer time horizon after the tax would be needed to identify the long-run equilibrium. For example, Hall, Horton and Knoepfle (2021) show that after an Uber-initiated price increase, the adjustment of prices towards the long-run equilibrium required about two months. Thus, my empirical strategy imposes to interpret the results as the short-run effects of the tax. While long-run dynamics may be interesting, these would be impossible to capture in my setting because of the beginning of the COVID-19 pandemic in March 2020. Nevertheless, the short-run effects of this kind of taxes are important and worth being documented. First, when the transition to the long-term equilibrium takes considerable time, short-run changes can have substantial welfare implications. Second, documenting short-run responses can help comprehend the adjustment process toward the long-term equilibrium. Third, analyzing short-run responses can still provide important insights about demand and supply characteristics such as demand elasticity. For all these reasons, short-run responses to taxes have received considerable attention in the public and urban economics literature.[27]

5 The Heterogeneous Effects of the Tax

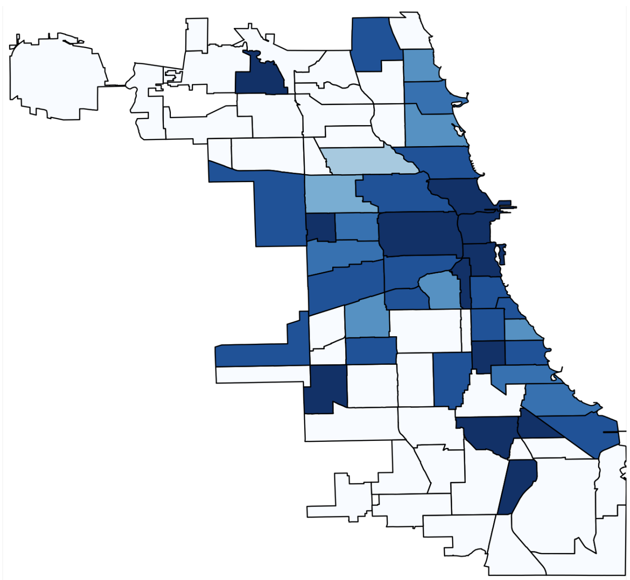
I begin by examining the heterogeneous impact of the tax on the price per trip of ride-sharing across originating CA and destination points. To that extent, I use the model presented in Equation 1 to estimate the average change in prices, defined as the total amount paid by riders, comprehensive of the tax, for trips starting from any CA and ending in the Loop, in an employment subcenter or any other CA.

Figure 2 summarizes the results of these analyses by showing for each CA of Chicago the price increase after the tax (in $ per ride) for trips starting in that CA and ending in the Loop, in an employment subcenter or in any other CA. CAs with no statistically significant change in price at the 5% level are rounded to zero. Figure 2 suggests that most CAs experienced significant increases in prices, and that such increases were heterogeneous across geographical endpoints. For each destination, there were CAs experiencing no price change, and others seeing increases larger than $1 per-ride, and in some cases, even larger than $2 per-ride.

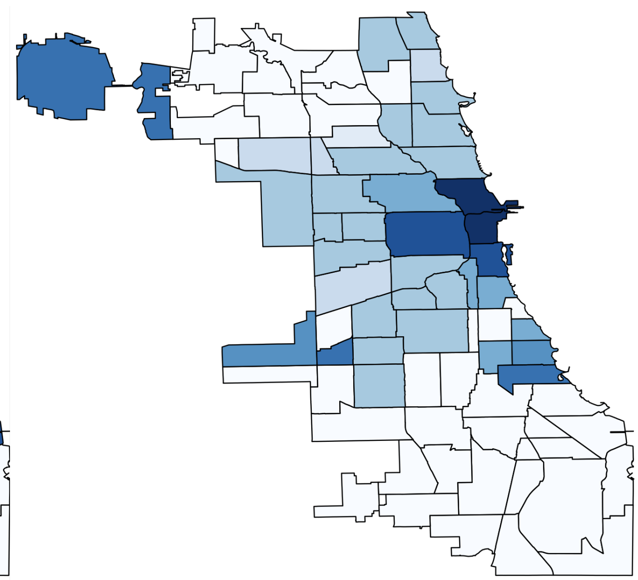
The destination of the trip also played a role in determining the variation in price changes.

[27]For example, the recent work by Almagro et al. (2024) structurally estimates a model to quantify the short-run responses to various transportation policies, whereas Hindriks and Serse (2019) examine the short-run impact of a tax on alcoholic beverages on the retail prices of six major brands of spirits.

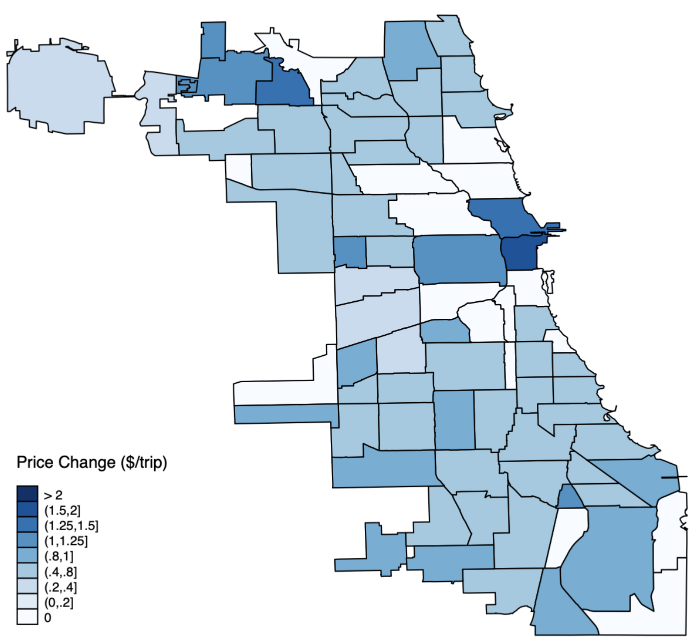
Figure 2: Estimated CA-level change in ride-sharing prices across destinations



(a) Trips to the Loop



(b) Trips to Employment Subcenters



(c) Other trips

Notes: The maps of Chicago illustrate the average increase in prices for trips originating in any CA and ending in the Loop, employment subcenters, or anywhere else. CAs with no statistically significant change in price at the 5% level are rounded to zero.

This is even more clear from Figure 3, which illustrates the average effect for trips to each destination point, as well as the overall effect. For trips to CAs outside the Loop that were not employment subcenters, most CAs experienced price changes between \$0.40 and \$1.25. However, conditional on a price change occurring, the change in prices tended to be higher for trips to employment subcenters. Trips to the Loop faced even larger price increases, which was not surprising since the tax increase for these rides was larger than that for all other rides (\$2.28 versus \$0.53).[28]

In effect, a given price increase corresponded to a much larger pass-through rate for trips to employment subcenters or any other area compared to trips to the Loop. For example, a \$1 increase in price corresponded to pass-through rates of 43.86% and 188.68% for trips ending in the Loop and anywhere else, respectively.[29] However, not all trips to the Loop faced larger price increases. For instance, the price increase for trips to the Loop starting in the O'Hare airport's CA was lower than that for trips starting in the same CA and ending in any CA not classified as an employment subcenter, which in turn was lower than that for trips from O'Hare ending in an employment subcenter.

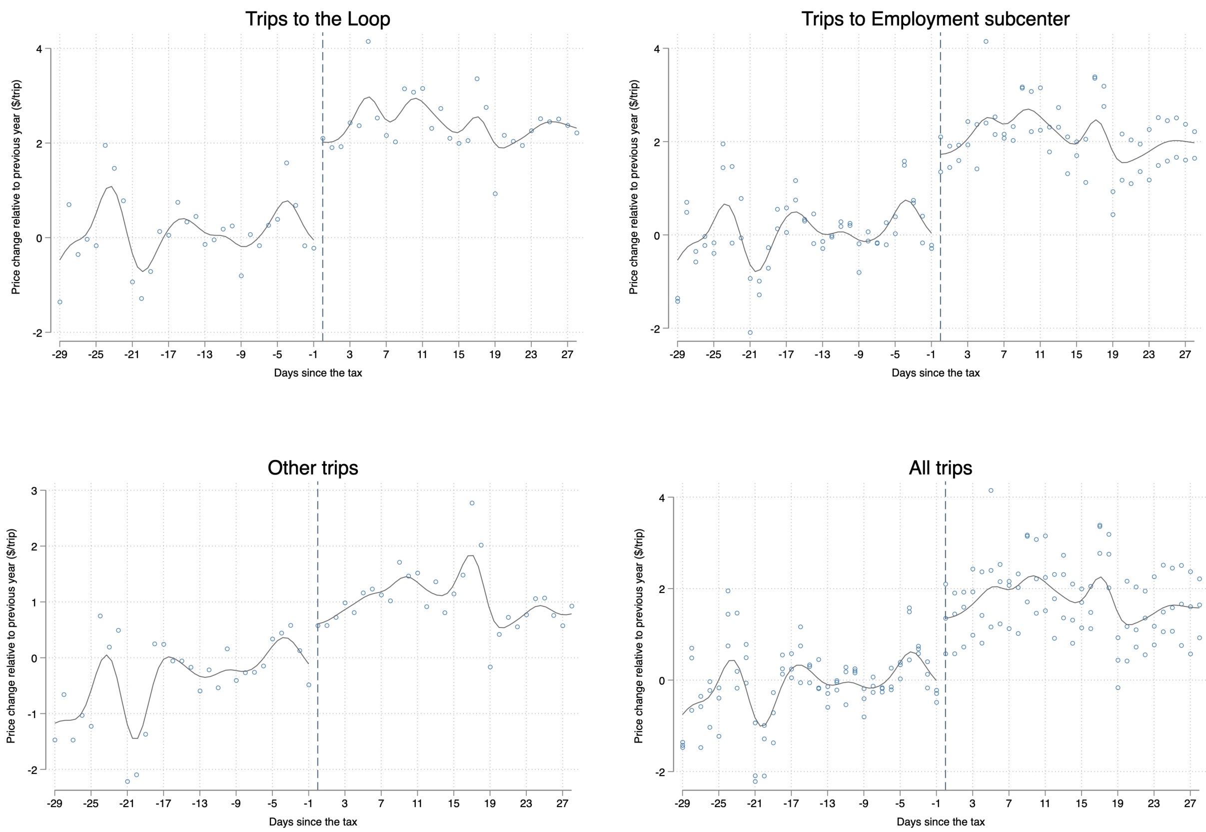
Furthermore, the set of CAs that saw price increases after the tax implementation appeared similar between trips to the Loop and employment subcenters, whereas for all the other trips price increases were more widespread across CAs, affecting most south and northwest CAs of Chicago with increases higher than \$0.40 per trip.

A natural policy-related question is what drives the observed difference in price changes across CAs. To take a step towards answering this question, I test whether differential access to transportation means other than ride-sharing is correlated with estimated price changes. Intuitively, since for every trip passengers choose the preferred transportation mean in their choice set (e.g., public transit, private car, or ride-sharing), the extent to which ride-sharing apps pass the tax on to riders will also depend on the availability and

[28]The same tax increase was experienced by trips starting in the Loop.

[29]Pass-through rates are computed by dividing the change in the price caused by the tax by the increase in the tax amount charged.

Figure 3: Average change in TNP prices across destinations



Notes: Each figure visualizes the change in the average price of ride-sharing relative to the the price paid on the corresponding day in the previous year at the tax implementation cutoff for different types of rides.

convenience of alternatives to ride-sharing.[30]

Effectively, I implement an estimated dependent variable model (Lewis and Linzer, 2005), where I regress the estimated CA-level change in prices on covariates that reflect the availability of alternative means of transportation in the CA.[31] In particular, for each of the three destinations considered (i.e., the Loop, an employment subcenter or any other CA), I run the following regression:

$$\hat{\beta}_j = \alpha_1 \cdot \text{Income}_j + \alpha_2 \cdot \text{LTrain}_j + \alpha_3 \cdot \text{Car} + +\boldsymbol{Z_j'} \cdot \boldsymbol{\xi} + \eta_j \tag{2}$$

where $\hat{\beta}_j$ is obtained estimating Equation 1 for trips starting in CA j; Income is the median income (in \$000) of the CA j (namely the one wherein trips originate); LTrain approximates access to public transit in CA j by measuring the number of LTrain stops per square mile located in the CA; Car is a proxy for the availability of private cars in CA j as it measures the percentage of households residing in the CA with at least one private car. In addition, $\boldsymbol{Z}$ includes control for the presence of an airport in the CA, taxi and pooled ride-sharing service usage.[32]

Table 2 reports the results of these regressions. In Column (1) the dependent variable is the estimated price increase for trips starting in any CA and ending inside the Loop. Since the dynamics of demand in the Loop may be very different from those in the other CAs due to the high concentration of both private- and public-sector jobs in the area, I exclude from this regression trips having the Loop as the starting CA. I find that a marginal increase in the number of LTrain stops per square mile is correlated with almost a \$0.30 lower average

[30] A large body of literature has studied how ride-sharing affected public transit and private cars usage, showing that ride-sharing tends to a substitute for private cars and rapid transit but a complement to buses (Hall, 2018; Stiglic et al., 2018; Erhardt et al., 2019; Djavadian, Farooq and Meshkani, 2021; Gonzalez-Navarro et al., 2022; Agrawal and Zhao, 2023).

[31] In this analysis, I weight the CA-level regression by an inverse function of the uncertainty of the model estimates.

[32] Airports in Chicago are located in two CAs: O'Hare and Clearing. Taxi service usage is proxied by the natural log of the average number of daily taxi trips starting from the CA in any weekday—excluding holidays—between 11/1/2019 and 12/31/2019, whereas the natural log of the average number of daily shared TNP trips starting from the CA in any weekday—excluding holidays—between 11/1/2019 and 12/31/2019 proxies pooled ride-sharing service usage.

Table 2: Correlation between estimated CA-level price change and CA's characteristics

VARIABLES	(1) Rides to the Loop	(2) Rides to Employment Subcenters	(3) Other rides
Income	0.008**	0.003	0.001
	(0.0037)	(0.0027)	(.00023)
LTrain	-0.291***	-0.030*	-0.058***
	(0.0890)	(0.0174)	(0.0189)
Car	-0.022*	-0.014**	-0.005
	(0.0112)	(0.0056)	(0.0041)
Observations	76	77	77
R-squared	0.535	0.488	0.434

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the estimated change in the average price per ride for trips starting in any CA and ending in The Loop (Column (1)), employment subcenters (Column (2)), or any other CA (Column (3)). I exclude trips within the Loop. The covariates I consider include: the CA median income (in $000), the number of LTrain stops per square mile located in the CA, the percentage of households residing in the CA with at least one private car. In addition, I control for: the presence of an airport in the CA (this is the case for two CAs, i.e., O'Hare and Clearing), taxi service usage, proxied by the natural log of the average number of daily taxi trips starting from the CA in any weekday—excluding holidays—between 11/1/2019 and 12/31/2019, and usage of pooled ride-sharing services, proxied by the natural log of the average number of daily shared TNP trips starting from the CA in any weekday — excluding holidays — between 11/1/2019 and 12/31/2019. Robust standard errors are reported in parentheses.

price increase after the tax. These results suggest that varying access to alternatives to ride-sharing, particularly the Ltrain, and to a lesser extent, private vehicles, significantly contributes to the observed differences in price increases across different CAs.

Nonetheless, such factors influencing the elasticity of demand are not the sole drivers of pass-through. Supply elasticity can also play a crucial role, particularly in the ride-sharing industry. As drivers move across CAs to pick up passengers, they might respond to the initial different price increases—which affect their hourly earnings—by adjusting their supply across CAs. Specifically, since trips originating in CAs with more elastic demand will experience a lower increase in prices, more drivers might shift their focus to CAs with less elastic demand, thus leading to an increase in the supply of rides in these CAs relative to those with more elastic demand. This can result in a reduction in the price of trips starting in CAs with less elastic demand compared to those from CAs with more elastic demand, mitigating the initial demand-driven price effect. Therefore, in practice, my analyses empirically identify the short-run net effect of these two forces.[33] Although further adjustments on the supply side may reduce heterogeneity in pass-through across CAs in the long-run, I demonstrate that such disparities persist in the short term, have economic significance, and are at least in part attributable to differential access to alternatives to ride-sharing.

6 The Impact of the Tax on Racial Areas

The results of the previous analyses support the notion that the variability in price increases following the tax was, to some extent, influenced by varying access to alternative transportation options across CAs. Building on this observation and taking into account the distribution of different racial groups across CAs with differing degrees of access to public transit and private vehicles, this section aims to explore whether the tax had disproportionate effects on CAs with distinct racial compositions.[34]

To explore the impact of the tax on areas in which different racial groups are concentrated, I classify CAs into four racial areas—Asian, Black, Hispanic, or White. A CA is assigned to a racial area if 60% or more of its population belongs to that race. This approach allows me to examine the heterogeneous effects of the tax on ride-sharing prices and usage for various types of rides across different racial areas. As in the previous analyses, I analyze trips to the Loop, employment subcenters, and other CAs, while further distinguishing them by the time of day. Specifically, trips between 6AM and 10AM are labeled as work-schedule, while all other rides are considered leisure-schedule.

It is important to note that the method used to identify racial areas in this study does not account for the possible correlation between a passenger's race and their likelihood of using ride-sharing services. For instance, it is possible that in a predominantly Black CA, most ride-sharing users are actually White residents. Therefore, the estimated effects of

[33] The lack of driver-level data prevents me from distinguishing the contribution of each channel.

[34] For example, as shown in Figure B.3, residents of predominantly Black areas—i.e., areas where 60% or more of the population is black—are more likely to have no access to private cars and have worse access to the Ltrain than residents of predominantly White CAs.

the tax on different racial areas do not directly reflect the effects on specific racial groups. Estimating the effects of the tax on different racial groups would require access to data on the race of the passenger for each trip record, which is not available in this study.

However, an increase in ride-sharing prices in a given racial area can still reduce the number of residents who use the service and decrease the probability that non-users will start using it. This can limit the urban mobility options of the predominant racial group and have negative consequences regardless of their previous use of ride-sharing. Therefore, an increase in ride-sharing prices in a specific racial area can disproportionately harm the predominant racial group by limiting their urban mobility capabilities.

6.1 Effects on Ride-sharing Prices

To identify the effects of the tax on trips starting from any racial area, I re-estimate the same model of Equation 1 for each type of ride considered (e.g., a work-schedule ride starting in the Hispanic area and ending in the Loop).

Table 3 summarizes the estimated effect of the tax on the final prices paid by riders, comprehensive of the tax. In the top panel, columns (1)–(4) refer to work–schedule trips to the Loop starting in any of the for racial areas, while columns (5)–(8) to leisure–schedule trips to the Loop starting in any of the for racial areas. Similarly, in the middle (bottom) panel, columns (1)–(4) refer to work–schedule trips to employment subcenters (any other CA) starting in any of the racial areas, while columns (5)–(8) to leisure–schedule trips to employment subcenters (any other CA) starting in any of the for racial areas. Robust standard errors are reported in parentheses.

I find that prices significantly increased for all types of rides, except those during work–schedule starting in the Asian area and ending outside the Loop in CAs that are not employment subcenters, and such increases were very heterogeneous across types of rides.

Price increases were larger for rides to the Loop due to the larger tax amount levied on these rides: depending on the racial area where the ride began, the average increase in price

Table 3: Estimated price changes

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
Rides to the Loop								
β	1.827***	2.430***	1.993***	1.993***	2.333***	2.440***	2.257***	2.063***
	(0.1836)	(0.0659)	(0.0711)	(0.0342)	(0.1005)	(0.0625)	(0.0705)	(0.0310)
Observations	3,276	55,846	36,920	293,849	11,159	58,796	34,122	221,812
R-squared	0.496	0.710	0.772	0.425	0.516	0.728	0.780	0.559
Rides to Employment Subcenters								
β	1.151***	1.464***	1.082***	1.435***	1.742***	1.342***	1.233***	1.126***
	(0.1545)	(0.0360)	(0.0351)	(0.0212)	(0.0758)	(0.0280)	(0.0257)	(0.0092)
Observations	10,170	229,250	177,800	1,077,732	43,426	382,777	303,579	2,645,806
R-squared	0.786	0.839	0.840	0.750	0.762	0.853	0.860	0.831
Other Rides								
β	0.565	0.931***	0.760***	0.722***	0.854***	0.908***	0.880***	0.741***
	(0.3886)	(0.0227)	(0.0418)	(0.0951)	(0.1337)	(0.0152)	(0.0270)	(0.0265)
Observations	3,613	311,910	103,555	122,150	16,441	771,572	249,479	443,522
R-squared	0.919	0.890	0.897	0.792	0.913	0.893	0.898	0.865

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: β is the effect of the tax on prices ($ per ride). In the top panel, columns (1)–(4) refer to work-trips to The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to The Loop starting in any of the four racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work-trips to any CA excluding The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to any CA excluding The Loop starting in any of the four racial areas. The results refer to the preferred specification with a 29 days bandwidth. All regressions use data at the trip-level and include controls for weather, distance of the trip (in miles) and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

for a trip to the Loop ranged between \$1.83 and \$2.44, while the range was \$1.08–\$1.74 for trips to employment subcenters, and \$0–\$1.18 for trips to any other CA. For example, the price of a work-schedule trip starting in the Hispanic area and ending in an employment subcenter increased on average by \$1.08—which corresponds to a 7.48% increase. A similar trip experienced an average increase of \$1.99, corresponding to a 12.93% increase when ending inside the Loop, and of \$0.76 (i.e., a 5.78% increase) when ending in any other CA that is not an employment subcenter.[35] However, price changes also differ across time windows. In this regard, one might expect work-schedule trips to experience higher price increases than leisure-schedule trips due to a less elastic demand, but I find that this is not always the case. For example, a trip from the Hispanic area to the Loop experienced an average price increase of \$1.93 if taken during work–schedule, while the price increase for a similar leisure–schedule ride was \$2.26. A possible explanation for these findings could be that some alternative transportation means—e.g., public transit—function more efficiently during work–schedule hours, thus making demand for ride-sharing from some CAs more elastic.

Remarkably, Table 3 shows that Black areas suffered the largest price increases. Excluding trips to employment subcenters during leisure–schedule, for which trips starting from the Asian area experienced the largest price increase (\$1.74), residents of Black areas were the ones experiencing the largest price increases for every type of ride.[36] Such increases ranged from \$0.91 for leisure–schedule rides to CAs outside the Loop that are not employment subcenters to \$2.44 for leisure–schedule rides to the Loop. In contrast, trips starting in White areas tended to have lower price increases, ranging between \$0.72 and \$2.06. Although my focus is on the short-term effects of taxing ride-sharing, my findings suggest that taxes such as the one implemented in Chicago could worsen racial segregation in the long-run since changes in transportation costs can alter the spatial organization of cities (Tsivanidis, 2018; Bryan, Glaeser and Tsivanidis, 2020).

[35] Percentage price changes are computed using pre-tax average prices per trip reported in Table 1.

[36] I conduct statistical tests for the difference of the coefficient compared. Table A.2 reports the results and shows that in all cases but trips to other CAs during the leisure-schedule, Black CAs faced higher increases in prices.

In the adopted identification strategy, the choice of the length of the subsamples that I pool together, which corresponds to the choice of the bandwidth in a RDiT design, is arbitrary. I choose 29 days for the main specifications, following examples in the RDiT literature—for instance, Anderson (2014) chooses 28 days. Therefore, as a robustness check, I rerun the same regressions using different bandwidths between 24 and 34 days around the cutoff dates. Tables A.7 and A.8 in the Appendix show that the estimates are robust.

Another potential concern is that estimates of β could reflect secular spatial changes in travel patterns. Specifically, if the spatial composition of trips changed in a way that is not perfectly captured by the trip length—which I control for in Equation (1)—it may well be in a way that is correlated with the treatment. To address this, I run an additional set of regressions adding origin-destination CA-pair fixed-effects to the baseline model. This allows me to control for any time-invariant origin-destination-specific factor that might confound β, including the distance-related determinants of price that might not be captured by the linear control for distance included in $\boldsymbol{X_t}$. Moreover, since one may argue that robust standard errors may not allow for sufficient correlation in the error covariance matrix, in these specifications I also cluster standard errors by CA origin-destination pair over time. This allows errors to be correlated before and after treatment. The results of these additional regressions are summarized in Table A.6 and are consistent with the results in Table 3, showing that in practice all these potential concerns do not affect the results of the main specification considered.

Lastly, when categorizing CAs into racial groups based on ride origins, the paper faces the challenge of determining which area bears the burden of return trips. Unfortunately, the lack of rider identifiers or information on their residential CA prevents the identification of return trips and hence my ability to fully address this concern. However, replicating the analysis by clustering destination CAs into racial areas and comparing the results with those from clustering origin CAs indicates the robustness of the main findings. The results of this check are summarized in Table A.12.

6.2 Effects on Ride-sharing Usage

Learning how residents of different racial areas respond to changes in the cost of using ride-sharing can provide key insights into their underlying demand and help guide future policies.[37] Thus, I next examine riders' responses to the increase in prices following the tax.

To that end, I first estimate the same regression of Equation 1, where Y_t now represents the natural logarithm of the number of TNP rides in a given day, and I rename β—the effect of the tax on the dependent variable—β_q to ease exposition.[38] The unit of this regression is a day, and hence in the main specification, I have 116 observations. This follows from the fact that I use a bandwidth of 29 days, and I pool together Sample 18-29 and Sample 19-20, each of length 58 days (29×2).

Table 4 reports estimates of β_q for different types of rides. In the top (middle) panel, columns (1)–(4) refer to work-schedule trips to the Loop (employment subcenters) starting from Asian, Black and White areas, respectively, while columns (5)–(8) refer to leisure–schedule trips to the Loop (employment subcenters) starting in any of the four racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work–schedule trips to any other CA starting in any of the four racial areas, while columns (5)–(8) to leisure–schedule trips to any other CA starting in any of the four racial areas. Robust standard errors are reported in parentheses.

As demonstrated in Table 4, there was no statistically significant (at the 5% level) reduction in the number of trips originating from Asian and White areas, except for rides from White areas to employment subcenters, where I observed a 9.34% decrease.[39] In contrast, I noted considerable and statistically significant reductions in the equilibrium number of trips originating from Black and Hispanic areas, except for work-schedule rides ending in CAs that are not employment subcenters and for work-schedule rides originating from the Hispanic

[37]This applies to any group of users identifiable (e.g., via income or gender). For example, Christensen and Olsen (2021) focus on gender and find that women's demand for Uber usage is more elastic than that of men because they feel more unsafe using public transit.

[38]To account for changes in market trends due to the expansion of ride-sharing platforms, I augment the model with a linear calendar date trend.

[39]Percentage changes in the equilibrium number of trips are calculated as $\exp(\beta_q) - 1$.

Table 4: Effects of the tax on the number of rides

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
Rides to the Loop								
β_q	-0.184	-0.190**	-0.143*	-0.116	0.012	-0.183***	-0.109**	-0.032
	(0.1482)	(0.0672)	(0.0745)	(0.0767)	(0.1081)	(0.0387)	(0.0480)	(0.0400)
Observations	116	116	116	116	116	116	116	116
R-squared	0.478	0.773	0.764	0.782	0.698	0.841	0.839	0.855
Rides to Employment Subcenters								
β_q	-0.147	-0.138**	-0.135**	-0.098**	0.048	-0.132***	-0.112***	-0.080*
	(0.1143)	(0.0536)	(0.0510)	(0.0457)	(0.0980)	(0.0247)	(0.0304)	(0.0454)
Observations	116	116	116	116	116	116	116	116
R-squared	0.654	0.867	0.866	0.822	0.770	0.943	0.939	0.919
Other Rides								
β_q	-0.050	-0.127*	-0.098*	-0.072*	-0.143*	-0.125***	-0.076**	-0.063
	(0.1217)	(0.0723)	(0.0500)	(0.0393)	(0.0797)	(0.0310)	(0.0316)	(0.0372)
Observations	116	116	116	116	116	116	116	116
R-squared	0.830	0.798	0.885	0.849	0.778	0.948	0.958	0.906

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports coefficients estimating the effect of the tax on the log of the number of TNP rides (β_q). In the top panel, columns (1)–(4) refer to work-trips to The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to The Loop starting in any of the four racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work-trips to any CA excluding The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to any CA excluding The Loop starting in any of the for racial areas. The results refer to the preferred specification with a 29 days bandwidth. All regressions use daily data and include controls for weather, a linear calendar date trend and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

area and ending inside the Loop. Specifically, comparing point estimates suggests that rides starting from Black areas experienced larger percentage reductions, which is consistent with the higher price increases reported in Table 3. The most substantial reduction occurred for work-schedule trips to the Loop (-17.3%). However, as shown in Table A.3 of the Appendix, for most types of rides, the decline in ride-sharing usage in Black areas was not statistically different from that in Hispanic areas. I verify the robustness of these results by running regressions that use different bandwidths between 24 and 34 days around the cutoff dates. The estimates are generally robust, as demonstrated in Tables A.10 and A.11 in the Appendix.

Overall, my results show that the increase in prices following the tax translated into a decrease in ride-sharing usage mostly in Black and Hispanic areas. While the analysis focuses on the short-run effects of taxes on ride-sharing, my findings suggest that taxing ride-sharing may exacerbate existing disparities in urban mobility, which could have long-term impacts on racial and economic segregation.

6.3 Tax Incidence

This section offers insights into the distribution of the tax burden across various racial demographics. Despite the tax being levied on ride-sharing platforms, the substantial price hikes observed in the previous section suggest that riders may predominantly bear the burden of the tax.

To explore this further, I employ Equation 1 to estimate the aggregated impact on trips based solely on the racial composition of the respective CA of origin. Subsequently, I also re-estimate the equation distinguishing rides based on the tax increments faced, and hence separate rides to the Loop—which faced a \$2.28 per trip tax increment—from all the others—which faced a \$0.53 per trip tax increment. Table A.5 presents estimates of the overall price changes resulting from these analyses. The estimated increases in the total price paid by riders, comprehensive of the tax, are reported as Δp^{Rider} in Table 5.

Furthermore, with knowledge of the tax increment, I can calculate the \$ change in the average amount per trip earned by drivers and platforms, as well as the tax pass-through rate. The combined change in the amount per-trip received by platforms and drivers equals the difference between Δp^{Rider} and the tax increment. To separately identify platform and driver change in the price received, I assume that platforms collect 23.35% of the combined amount. This corresponds to the average per-trip fee charged by each ride-sharing company in the market, weighted by its market share. Tax pass-through is computed as the change in the final price induced by the tax Δp^{Rider}, divided by the increase in the tax amount levied. For instance, considering a trip from the Asian area to the Loop that experienced a \$2.17 price hike, with the tax rising from \$0.72 to \$3.00 per trip on these rides, I can calculate:

- $\Delta p^{\text{Platform}}$ as $\$\,[2.17 - (3 - 0.72)] \times 0.2335 = -\$0.03$;
- Δp^{Driver} as $\$\,[2.17 - (3 - 0.72)] \times (1 - 0.2335) = -0.08$; and
- tax pass-through rate as $\frac{\$2.17}{\$(3-0.72)} \times 100 = 95.35\%$.

Thus, for trips from the Asian area to the Loop, about 95% of the tax was borne by riders, 3.50% by drivers, computed as $\frac{-\Delta p^{\text{Driver}}}{\$(3-0.72)}$, and the rest by the platform.

Table 5 shows that the observed heterogeneity in price increases discussed in Section 6.1 directly translates into heterogeneous pass-through rates. Overall, the burden of the tax fell primarily on riders, with tax overshifting in all four racial areas. However, pass-through rates were notably higher in areas with a concentration of minorities, exceeding those in the White area by more than 36 percentage points. Pass-through rates tended to be lower for trips to the Loop, with the Black area being the sole exhibiting a pass-through rate surpassing 100%.

It is noteworthy that the pass-through rates displayed in Table 5 are often greater than 100%. While to explain such results traditional tax incidence analysis requires the presence of market power and strong assumptions on the shape of demand and the exact nature of competition to hold (Weyl and Fabinger, 2013), in the ride-sharing market, the existence of network externalities—which is a typical feature of online peer-to-peer-marketplaces—and the fact that ride-sharing companies are multi-product firms offering competing services (i.e.,

Table 5: Estimated tax incidence across racial areas

	(1) Asian	(2) Black	(3) Hispanic	(4) White
All trips				
Average pass-through (%)	165.70	162.27	142.18	105.71
Δp^{Rider} (\$ per trip)	1.28	0.98	0.90	0.81
Δp^{Driver} (\$ per trip)	0.39	0.29	0.21	0.03
$\Delta p^{\text{Platform}}$ (\$ per trip)	0.12	0.09	0.06	0.01
Trips to the Loop (\$2.28 tax increment)				
Average pass-through (%)	95.35	107.11	93.42	87.24
Δp^{Rider}(\$ per trip)	2.17	2.44	2.13	1.99
Δp^{Driver} (\$ per trip)	-0.08	0.12	-0.11	-0.22
$\Delta p^{\text{Platform}}$ (\$ per trip)	-0.03	0.04	-0.04	-0.07

Notes: Average pass-through and Δp^{Rider} are estimated in Table A.5. In the top panel, which considers all trips, rides to the"Near North Side" and the "Near West Side" are excluded because the exact tax increment cannot be identified.

single and pooled rides) make it easier to rationalize tax overshifting than in a traditional one-sided market with single-product firms (Agrawal and Hoyt, 2019; Leccese, 2022).

In summary, the findings presented underscore that the welfare costs of taxing ride-sharing were mainly borne by riders, especially in non-White areas. This indicates that taxing ride-sharing can have significant and heterogeneous welfare implications, possibly exacerbating racial disparities.

7 Conclusion

By combining data from various sources, this study demonstrates that, in Chicago, the effects of taxing ride-sharing were heterogeneous across the different areas of the city. First, I document significant variation in the impact of the tax on the total price paid by riders for a ride-sharing trip depending on the starting community area and destination, providing evidence that the observed heterogeneity was correlated with community areas' differential access to alternatives to ride-sharing, particularly public transit. Second, my analysis revealed that rides starting in Black areas had particularly high price increases, ranging from \$0.91 to \$2.44 per ride, while White areas experienced lower increases ranging from \$0.72 to \$2.06 per ride. Third, the increased ride-sharing costs resulting from the tax led to a reduction in ride-sharing trips exclusively from Black and Hispanic areas. Lastly, simple calculations show that the burden of the tax was primarily borne by areas with a higher concentration of minorities.

My findings contribute to ongoing policy debates by shedding light on the alleged trade-off between tackling negative externalities and the exacerbation of inequalities. In Chicago, policymakers penalized non–White, especially Black, CAs, and at the same time failed to reduce congestion (Leccese, 2022). The asymmetric reduction in the usage of ride-sharing across racial areas documented in this paper also suggests the possible arising of additional long-term costs associated with taxes on ride-sharing in terms of increased racial and economic segregation.

Since the reduction in urban mobility of some demographic groups would be the most likely propagation mechanism for this effect, a more complete investigation of commuters' preferences and implied substitution patterns across transportation means via a structural framework could be a natural next step for future research. More broadly, examining the impact on racial and income inequality of policies aimed at correcting externalities offers a number of directions for future work.

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ONLINE APPENDICES FOR

"Taxing Ride-sharing: Which Neighborhoods Pay More?"

by Mario Leccese

Appendix A Additional Tables

Table A.1: List of Employment Subcenters

Area ID	Area Name	Number of Jobs
1	Rogers Park	10,651
2	West Ridge	11,088
3	Uptown	12,696
5	North Center	11,541
6	Lake View	25,133
7	Lincoln Park	23,468
8	Near North Side	177,964
10	Norwood Park	13,557
19	Belmont Cragin	10,791
22	Logan Square	18,079
24	West Town	42,055
25	Austin	13,230
28	Near West Side	125,239
30	South Lawndale	11,342
31	Lower West Side	13,848
32	The Loop	420,089
33	Near South Side	14,066
41	Hyde Park	26,078
56	Garfield Ridge	12,798
61	New City	11,806
76	O'Hare	46,924

Table A.2: Statistical tests of coefficients equality for differential effects of the tax on prices across racial areas

	(1) Black = Asian	(2) Black = Hispanic	(3) Black = White	(4) Hispanic = White	(5) Asian = Hispanic	(6) Asian = White
Work / Loop	0.002***	0.000***	0.000***	0.997	0.395	0.371
Work / Emp. sub.	0.057*	0.000***	0.022**	0.001***	0.672	0.184
Work / Other	0.345	0.000***	0.033**	0.709	0.616	0.694
Leisure / Loop	0.365	0.052*	0.000***	0.012**	0.537	0.010***
Leisure / Emp. sub.	0.000***	0.020**	0.000***	0.000***	0.000***	0.000***
Leisure / Other	0.690	0.361	0.000***	0.000***	0.853	0.406

Notes: The table shows the p-value resulting from testing for significant differences of the β coefficients reported in Table 3.

Table A.3: Statistical tests of coefficients equality for differential effects of the tax on pickups across racial areas

	(1) Black = Asian	(2) Black = Hispanic	(3) Black = White	(4) Hispanic = White	(5) Asian = Hispanic	(6) Asian = White
Work / Loop	0.961	0.135	0.047**	0.512	0.688	0.524
Work / Emp. sub.	0.912	0.855	0.140	0.115	0.885	0.594
Work / Other	0.420	0.344	0.216	0.370	0.622	0.822
Leisure / Loop	0.045**	0.053*	0.000***	0.034**	0.021**	0.638
Leisure / Emp. sub.	0.023**	0.220	0.134	0.271	0.034**	0.077*
Leisure / Other	0.798	0.001***	0.005***	0.561	0.310	0.184

Notes: The table shows the p-value resulting from testing for significant differences of the β_q coefficients reported in Table 4.

Table A.4: Aggregated effects on prices and tax pass-through across racial areas

	(1) Asian	(2) Black	(3) Hispanic	(4) White
		Trips to the Loop		
β	2.174***	2.442***	2.130***	1.989***
	(0.0903)	(0.0475)	(0.0521)	(0.0247)
Pass-through	95.35%	107.11%	93.42%	87.24%
Observations	14,435	114,642	71,042	515,661
R-squared	0.518	0.702	0.762	0.451
		Other Trips		
β	1.015***	0.884***	0.783***	0.580***
	(0.1008)	(0.0123)	(0.0183)	(0.0131)
Pass-through	191.51%	166.79%	147.74%	109.43%
Observations	39,347	1,399,650	622,880	2,556,664
R-squared	0.870	0.888	0.881	0.832
		All Trips		
β	1.284***	0.983***	0.899***	0.806***
	(0.0796)	(0.0120)	(0.0175)	(0.0119)
Pass-through	165.70%	162.27%	142.18%	105.71%
Observations	53,782	1,514,292	693,922	3,072,325
R-squared	0.861	0.883	0.874	0.813

Notes: The table shows the results of regressions similar to those whose results are summarized in Table 3. The only difference is that trips across racial areas are not aggregated by time of the day. In the top and middle panel I distinguish them based on the tax increment ($2.28 for the Loop, $0.53 for the others), while all trips all pooled together in the bottom panel. Trips to the"Near North Side" and the "Near West Side" are excluded because the exact tax increment cannot be identified.

Table A.5: Aggregated effects on pickups and tax pass-through across racial areas

	(1) Asian	(2) Black	(3) Hispanic	(4) White
		Trips to the Loop		
β_q	-0.038	-0.186***	-0.126**	-0.086
	(0.0925)	(0.0437)	(0.0527)	(0.0519)
Observations	116	116	116	116
R-squared	0.706	0.829	0.831	0.819
		Other Trips		
β_q	-0.019	-0.128***	-0.104***	-0.085**
	(0.0743)	(0.0321)	(0.0277)	(0.0331)
Observations	116	116	116	116
R-squared	0.794	0.935	0.947	0.910
		All Trips		
β_q	-0.021	-0.131***	-0.105***	-0.086**
	(0.0746)	(0.0321)	(0.0284)	(0.0315)
Observations	116	116	116	116
R-squared	0.783	0.931	0.944	0.907

Notes: The table shows the results of regressions similar to those whose results are summarized in Table 4. The only difference is that trips across racial areas are not aggregated by time of the day. In the top and middle panel I distinguish them based on the tax increment ($2.28 for the Loop, $0.53 for the others), while all trips all pooled together in the bottom panel.

Table A.6: Estimated effect on prices including origin-destination fixed effects and clustering standard errors by the origin-destination pair over time

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
Rides to the Loop								
β	1.827***	2.452***	1.986***	1.986***	2.333***	2.427***	2.316***	2.059***
	(0.2114)	(0.1019)	(0.1354)	(0.1734)	(0.1326)	(0.0719)	(0.0866)	(0.0921)
Observations	3,276	55,846	36,920	293,849	11,159	58,796	34,122	221,812
R-squared	0.496	0.722	0.786	0.428	0.516	0.749	0.799	0.566
Rides to Employment Subcenters								
β	1.210***	1.508***	1.113***	1.428***	1.704***	1.398***	1.277***	1.141***
	(0.2185)	(0.0518)	(0.0612)	(0.0996)	(0.1308)	(0.0393)	(0.0474)	(0.0570)
Observations	10,169	229,230	177,795	1,077,725	43,426	382,771	303,577	2,645,802
R-squared	0.815	0.859	0.859	0.763	0.792	0.882	0.879	0.845
Other Rides								
β	0.894***	0.918***	0.838***	0.763***	0.721***	0.887***	0.848***	0.719***
	(0.1571)	(0.0223)	(0.0357)	(0.0745)	(0.0927)	(0.0151)	(0.0259)	(0.0344)
Observations	3,015	268,509	80,531	76,576	14,528	668,178	196,197	341,887
R-squared	0.891	0.868	0.887	0.759	0.868	0.875	0.886	0.830

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of regressions similar to those whose results are summarized in Table 3. The only differences are that: (i) The results reported in this table refer to regressions including CA origin and destination fixed effects; (ii) Standard errors are clustered by origin–destination pair over time.

Table A.7: Estimated effects of the tax on TNP price per trip with a longer bandwidth

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
	Rides to the Loop							
β	1.564***	2.084***	1.702***	1.683***	2.351***	2.393***	2.208***	2.028***
	(0.1789)	(0.0619)	(0.0667)	(0.0320)	(0.0935)	(0.0560)	(0.0659)	(0.0289)
Observations	3,821	65,669	43,540	343,659	13,122	69,643	40,347	261,211
R-squared	0.491	0.708	0.769	0.423	0.520	0.723	0.776	0.554
	Rides to Employment Subcenters							
β	0.907***	1.118***	0.837***	1.111***	1.685***	1.309***	1.183***	1.085***
	(0.1452)	(0.0343)	(0.0330)	(0.0202)	(0.0704)	(0.0259)	(0.0240)	(0.0086)
Observations	11,855	269,937	209,363	1,265,302	51,193	453,333	358,381	3,118,475
R-squared	0.787	0.839	0.840	0.752	0.755	0.851	0.857	0.830
	Other Rides							
β	0.387	0.762***	0.545***	0.257***	0.765***	0.893***	0.848***	0.695***
	(0.3451)	(0.0216)	(0.0391)	(0.0905)	(0.1250)	(0.0142)	(0.0251)	(0.0248)
Observations	4,276	366,833	121,920	143,510	19,400	906,506	293,099	520,650
R-squared	0.912	0.889	0.898	0.793	0.914	0.893	0.898	0.865

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: β is the effect of the tax on prices ($ per ride). In the top panel, columns (1)–(4) refer to work-trips to The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to The Loop starting in any of the for racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work-trips to any CA excluding the Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to any CA excluding The Loop starting in any of the four racial areas. The results refer to the specification with a 34 days bandwidth. All regressions use data at the trip-level and include controls for weather, distance of the trip (in miles) and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

Table A.8: Estimated effects of the tax on TNP price per trip with a shorter bandwidth

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
				Rides to the Loop				
β	1.699***	2.377***	2.033***	1.973***	2.334***	2.565***	2.226***	2.078***
	(0.2010)	(0.0724)	(0.0778)	(0.0379)	(0.1112)	(0.0663)	(0.0786)	(0.0338)
Observations	2,659	45,789	30,272	243,255	9,290	47,827	27,843	182,118
R-squared	0.493	0.719	0.781	0.440	0.532	0.743	0.785	0.563
				Rides to Employment Subcenters				
β	1.116***	1.423***	1.090***	1.457***	1.787***	1.411***	1.273***	1.113***
	(0.1815)	(0.0399)	(0.0391)	(0.0236)	(0.0837)	(0.0309)	(0.0284)	(0.0102)
Observations	8,138	187,690	145,430	887,951	35,909	311,527	247,828	2,166,649
R-squared	0.794	0.842	0.843	0.757	0.766	0.855	0.860	0.831
				Other Rides				
β	0.598	0.843***	0.721***	0.757***	1.052***	0.905***	0.911***	0.773***
	(0.4553)	(0.0252)	(0.0469)	(0.1068)	(0.1430)	(0.0167)	(0.0301)	(0.0291)
Observations	2,980	255,563	84,454	100,115	13,559	632,808	204,242	364,210
R-squared	0.928	0.892	0.898	0.797	0.912	0.895	0.898	0.865

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: β is the effect of the tax on prices ($ per ride). In the top panel, columns (1)–(4) refer to work-trips to The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to The Loop starting in any of the for racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work-trips to any CA excluding the Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to any CA excluding The Loop starting in any of the four racial areas. The results refer to the specification with a 24 days bandwidth. All regressions use data at the trip-level and include controls for weather, distance of the trip (in miles) and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

Table A.9: Robustness check for estimated price changes controlling for calendar date trend

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
				Rides to the Loop				
β	2.378***	2.890***	2.543***	2.408***	2.423***	2.803***	2.554***	2.423***
	(0.2023)	(0.0731)	(0.0797)	(0.0386)	(0.1117)	(0.0692)	(0.0801)	(0.0355)
Observations	3,276	55,846	36,920	293,849	11,159	58,796	34,122	221,812
R-squared	0.501	0.711	0.773	0.426	0.516	0.729	0.780	0.560
				Rides to Employment Subcenters				
β	1.601***	1.862***	1.462***	1.767***	1.948***	1.703***	1.457***	1.301***
	(0.1746)	(0.0400)	(0.0393)	(0.0238)	(0.0847)	(0.0321)	(0.0295)	(0.0104)
Observations	10,170	229,250	177,800	1,077,732	43,426	382,777	303,579	2,645,806
R-squared	0.786	0.840	0.840	0.750	0.762	0.854	0.860	0.832
				Other Rides				
β	1.643***	0.796***	0.797***	1.236***	0.888***	0.845***	0.815***	0.911***
	(0.5323)	(0.0257)	(0.0469)	(0.1070)	(0.1509)	(0.0171)	(0.0308)	(0.0302)
Observations	3,613	311,910	103,555	122,150	16,441	771,572	249,479	443,522
R-squared	0.920	0.890	0.897	0.792	0.913	0.893	0.898	0.866

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: β is the effect of the tax on prices ($ per ride). In the top panel, columns (1)–(4) refer to work-trips to The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to The Loop starting in any of the four racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work-trips to any CA excluding The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to any CA excluding The Loop starting in any of the four racial areas. The results refer to the preferred specification with a 29 days bandwidth. All regressions use data at the trip-level and include controls for weather, distance of the trip (in miles), a calendar date trend and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

Table A.10: Effect on the number of rides with a longer bandwidth

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
Rides to the Loop								
β_q	-0.167	-0.187***	-0.127*	-0.105	0.016	-0.201***	-0.094**	-0.036
	(0.1377)	(0.0644)	(0.0717)	(0.0747)	(0.1049)	(0.0397)	(0.0458)	(0.0367)
Observations	136	136	136	136	136	136	136	136
R-squared	0.462	0.780	0.775	0.775	0.703	0.828	0.836	0.860
Rides to Employment Subcenters								
β_q	-0.109	-0.143**	-0.144***	-0.090*	0.016	-0.136***	-0.123***	-0.072
	(0.1058)	(0.0518)	(0.0495)	(0.0451)	(0.0905)	(0.0253)	(0.0282)	(0.0431)
Observations	136	136	136	136	136	136	136	136
R-squared	0.595	0.874	0.872	0.819	0.778	0.940	0.940	0.929
Other Rides								
β_q	0.015	-0.153**	-0.113**	-0.085**	-0.172**	-0.132***	-0.083**	-0.067**
	(0.1134)	(0.0719)	(0.0481)	(0.0375)	(0.0742)	(0.0291)	(0.0292)	(0.0331)
Observations	136	136	136	136	136	136	136	136
R-squared	0.815	0.784	0.884	0.850	0.794	0.945	0.959	0.914

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports coefficients estimating the effect of the tax on the log of the number of TNP rides (β_q). In the top panel, columns (1)–(4) refer to work-trips to The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to The Loop starting in any of the four racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work-trips to any CA excluding The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to any CA excluding The Loop starting in any of the four racial areas. The results refer to the specification with a 34 days bandwidth. All regressions use daily data and include controls for weather, a linear calendar date trend and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

Table A.11: Effect on the number of rides with a shorter bandwidth

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
Rides to the Loop								
β_q	-0.130	-0.162**	-0.145*	-0.085	0.037	-0.145***	-0.109*	-0.038
	(0.1707)	(0.0677)	(0.0762)	(0.0761)	(0.1100)	(0.0446)	(0.0586)	(0.0509)
Observations	96	96	96	96	96	96	96	96
R-squared	0.494	0.794	0.774	0.803	0.669	0.831	0.822	0.853
Rides to Employment Subcenters								
β_q	-0.122	-0.113*	-0.119**	-0.076	0.098	-0.098***	-0.086**	-0.071
	(0.1296)	(0.0564)	(0.0538)	(0.0481)	(0.1095)	(0.0274)	(0.0336)	(0.0509)
Observations	96	96	96	96	96	96	96	96
R-squared	0.626	0.870	0.861	0.842	0.750	0.938	0.932	0.907
Other Rides								
β_q	-0.168	-0.105	-0.065	-0.062	-0.128	-0.083**	-0.045	-0.031
	(0.1286)	(0.0764)	(0.0532)	(0.0453)	(0.0863)	(0.0310)	(0.0337)	(0.0405)
Observations	96	96	96	96	96	96	96	96
R-squared	0.850	0.806	0.888	0.848	0.756	0.946	0.955	0.893

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports coefficients estimating the effect of the tax on the log of the number of TNP rides (β_q). In the top panel, columns (1)–(4) refer to work-trips to The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to The Loop starting in any of the four racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work-trips to any CA excluding The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to any CA excluding The Loop starting in any of the four racial areas. The results refer to the specification with a 24 days bandwidth. All regressions use daily data and include controls for weather, a linear calendar date trend and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

Table A.12: Estimated effects of the tax on TNP price across racial areas clustered by CA origin or destination

	ORIGIN				DESTINATION			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
	Rides to the Loop				Rides from the Loop			
β	2.378***	2.847***	2.526***	2.379***	2.522***	2.771***	2.777***	2.640***
	(0.1002)	(0.0525)	(0.0585)	(0.0278)	(0.1206)	(0.0670)	(0.0841)	(0.0311)
Observations	14,435	114,642	71,042	515,661	13,586	76,607	43,762	380,949
R-squared	0.518	0.702	0.763	0.452	0.449	0.661	0.680	0.450
	Rides to Employment Subcenters				Rides from Employment Subcenters			
β	1.877***	1.766***	1.455***	1.438***	1.924***	1.514***	1.419***	1.439***
	(0.0770)	(0.0253)	(0.0239)	(0.0104)	(0.0849)	(0.0297)	(0.0288)	(0.0097)
Observations	53,596	612,027	481,379	3,723,538	50,012	477,698	377,285	3,406,799
R-squared	0.765	0.847	0.850	0.799	0.724	0.840	0.825	0.800
	Rides to other CAs				Rides from other CAs			
β	0.973***	0.834***	0.809***	0.996***	1.567***	1.020***	1.043***	0.996***
	(0.1517)	(0.0143)	(0.0258)	(0.0341)	(0.0724)	(0.0144)	(0.0332)	(0.0317)
Observations	20,054	1,083,482	353,034	565,672	71,920	1,387,330	255,580	373,480
R-squared	0.914	0.892	0.897	0.833	0.819	0.874	0.874	0.829

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: β is the effect of the tax on prices ($ per ride). Columns (1)–(4) refer to trips clustering CAs into racial areas based on the origin, whereas in columns (5)–(8) the clustering is done using the CA of destination. The different panels refer to the heterogeneous impact depending on whether the other endpoint of the ride is the Loop (top), an employment subcenter (middle) or any other CA (bottom). The results refer to the specification with a 29 days bandwidth. All regressions use data at the trip-level and include controls for weather, distance of the trip (in miles) and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

Table A.13: Estimated price changes at the daily level

	WORK-SCHEDULE				LEISURE-SCHEDULE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
Rides to the Loop								
β	2.311***	2.810***	2.537***	2.349***	2.421***	2.816***	2.550***	2.357***
	(0.3069)	(0.3948)	(0.2881)	(0.5082)	(0.1657)	(0.1408)	(0.1537)	(0.1840)
Observations	116	116	116	116	116	116	116	116
R-squared	0.840	0.859	0.869	0.786	0.956	0.965	0.960	0.922
Rides to Employment Subcenters								
β	1.309**	1.609***	1.181***	1.524***	1.724***	1.460***	1.270***	1.106***
	(0.5023)	(0.2839)	(0.2053)	(0.4261)	(0.2478)	(0.1577)	(0.1217)	(0.1488)
Observations	116	116	116	116	116	116	116	116
R-squared	0.809	0.782	0.759	0.853	0.779	0.893	0.899	0.893
Other Rides								
β	1.656***	0.784***	0.756***	1.220**	0.885***	0.837***	0.793***	0.758***
	(0.4965)	(0.1532)	(0.1519)	(0.5224)	(0.2175)	(0.1028)	(0.1200)	(0.1507)
Observations	116	116	116	116	116	116	116	116
R-squared	0.941	0.818	0.784	0.765	0.901	0.928	0.916	0.830

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

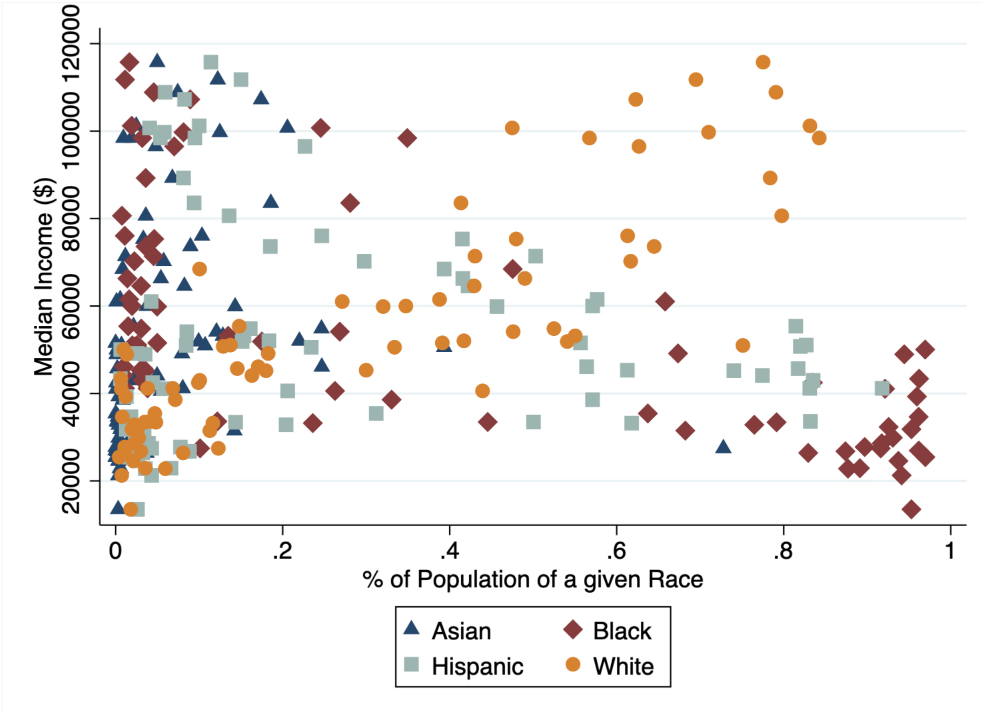
Notes: β is the effect of the tax on prices ($ per ride). In the top panel, columns (1)–(4) refer to work-trips to The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to The Loop starting in any of the four racial areas. Similarly, in the bottom panel, columns (1)–(4) refer to work-trips to any CA excluding The Loop starting in any of the four racial areas, while columns (5)–(8) to leisure-trips to any CA excluding The Loop starting in any of the four racial areas. The results refer to a specification with a 29 days bandwidth. All regressions use data aggregated at the day-level and include controls for weather, distance of the trip (in miles) and fixed effects for days of the week, weeks and months. Robust standard errors are reported in parentheses.

Appendix B Additional Figures

Figure B.1: Tax surcharge zone

Notes: The area within the dotted line identifies downtown the surcharge zone of the tax. The Loop is entirely contained in this surcharge zone. *Source: City of Chicago.*

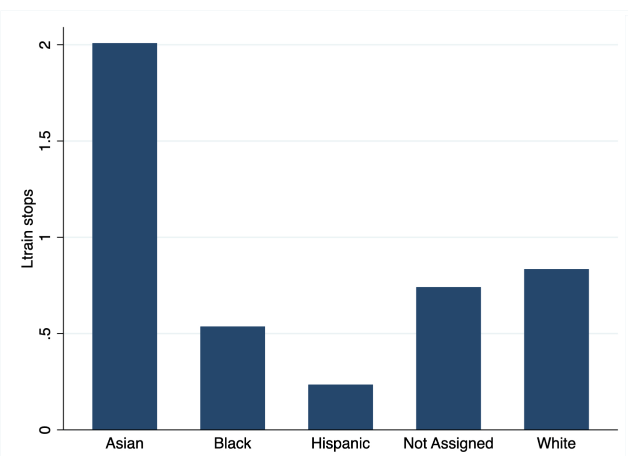
Figure B.2: Median income and race



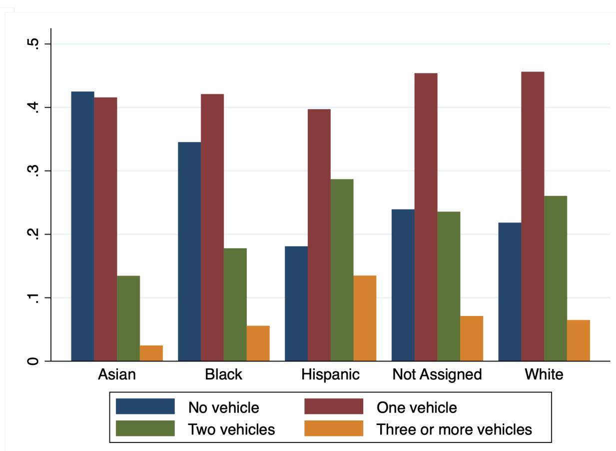
Notes: For each racial group considered, the figure illustrates the correlation between the median income in the CA and the percentage of population of a given race (Asian, Black, Hispanic or White) in that CA.

Figure B.3: Access to Ltrain and private vehicles across racial areas

(a) Acces to the Ltrain

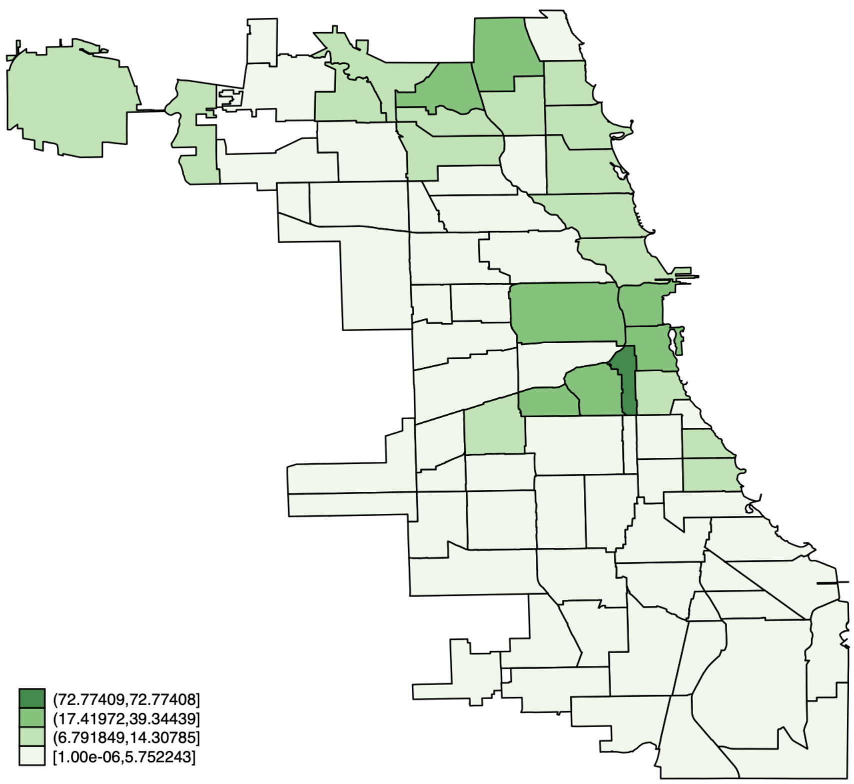


(b) Availability of private vehicles



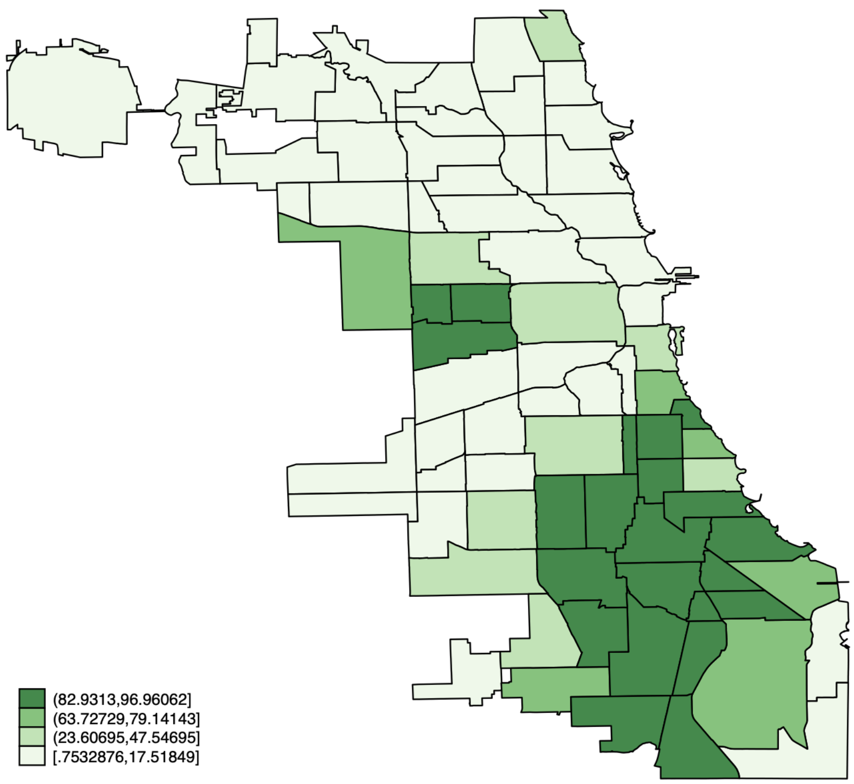
Notes: Panel (a) illustrates the average number of Ltrain stations per square mile in CAs across the different racial areas identified. Panel (b) shows the percentage of households with 0, 1, 2, and 3 or more private vehicles available in CAs across the different racial areas identified.

Figure B.4: Distribution of Asian population in Chicago



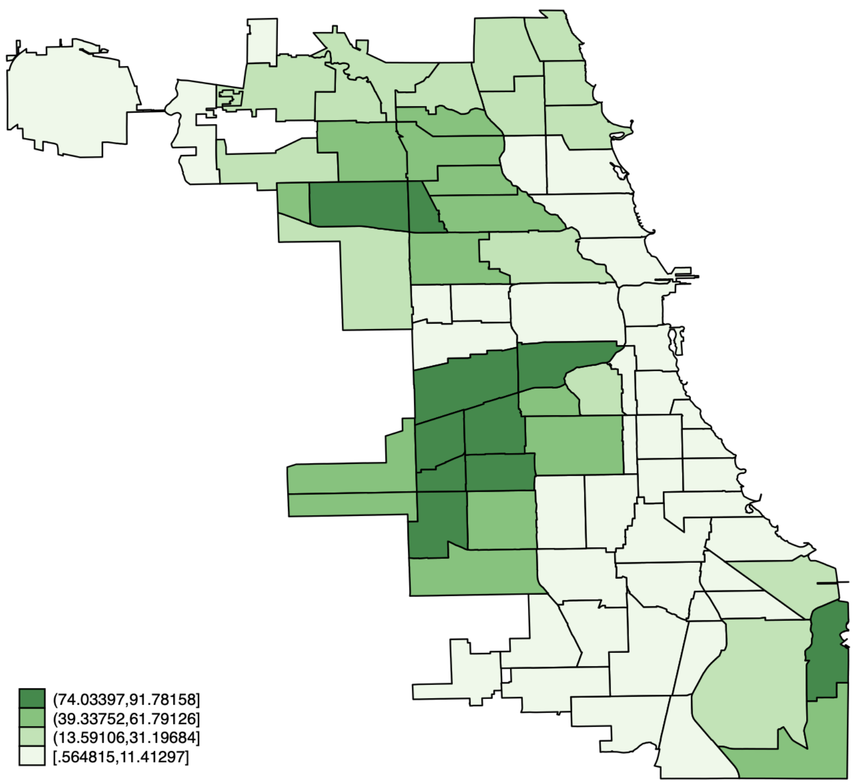
Notes: The map illustrates how CAs of Chicago are assigned to four different clusters in terms of percentage of White population via k-means clustering. The CA colored in the darkest shade of green is the only one composing the Asian area. The legend on the left of the figure reports the thresholds for the percentage of Asian population generated by the algorithm.

Figure B.5: Distribution of Black population in Chicago



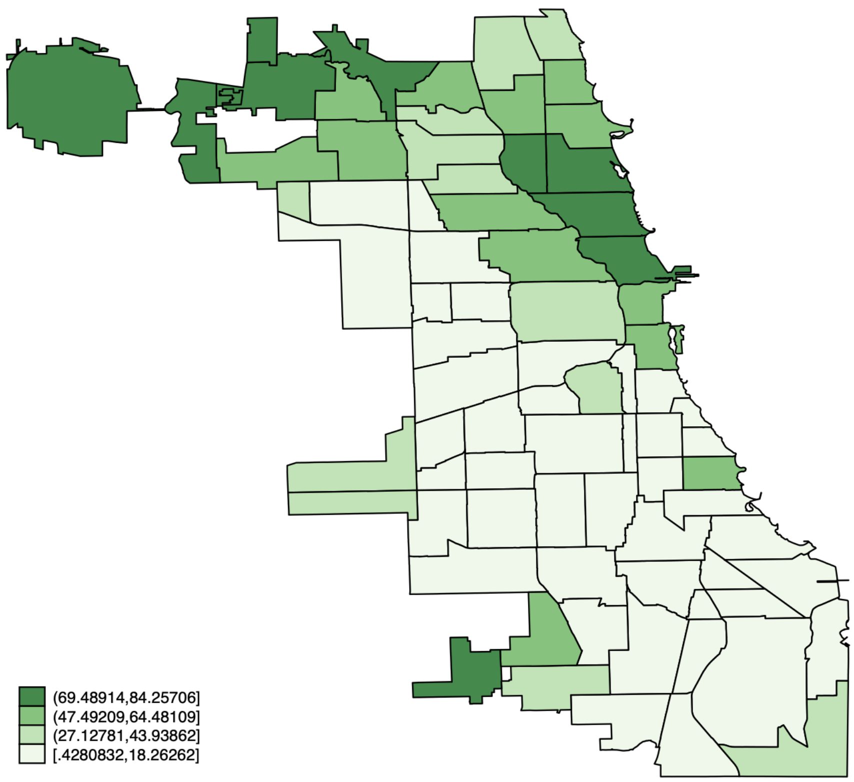
Notes: The map illustrates how CAs of Chicago are assigned to four different clusters in terms of percentage of Black population via k-means clustering. Areas colored in the darkest shade of green are those belonging to the Black area. The legend on the left of the figure reports the thresholds for the percentage of Black population generated by the algorithm.

Figure B.6: Distribution of Hispanic population in Chicago



Notes: The map illustrates how CAs of Chicago are assigned to four different clusters in terms of percentage of Hispanic population via k-means clustering. Areas colored in the darkest shade of green are those belonging to the Hispanic area. The legend on the left of the figure reports the thresholds for the percentage of Hispanic population generated by the algorithm.

Figure B.7: Distribution of White population in Chicago



Notes: The map illustrates how CAs of Chicago are assigned to four different clusters in terms of percentage of White population via k-means clustering. Areas colored in the darkest shade of green are those belonging to the White area. The legend on the left of the figure reports the thresholds for the percentage of White population generated by the algorithm. Note that, although O'Hare and the Near North Side would belong to the White area according to the results of the algorithm, I exclude them due to the presence of the main airport of the city and the impossibility to determine the exact tax amount, respectively.