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Do Minorities Pay More for Congestion Taxes? Evidence from a Tax on Ride-sharing

Mario Leccese*

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Abstract

I study the heterogeneous consequences across areas in which different racial groups are concentrated of a congestion tax on ride-sharing. I find that, on average, the price increase was the highest ($0.972/ride) for trips starting in Black areas, while it was the lowest ($0.750/ride) for trips starting in White areas. This is consistent with a larger elasticity of demand in White areas due to better access to public transit and wider availability of private vehicles across the population. Lastly, the tax reduced ride-sharing usage only in Black and Hispanic areas, and a simple back of the envelope calculation suggests that riders from Black areas were the most penalized by the tax, with an aggregate loss of over $17,000 per day.

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

JEL Classifications: H22, R22, R41, R48.

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1 Introduction

In recent years, the rapid growth in the usage of ride-sharing has reshaped the transportation landscape of many U.S. cities. While ride-sharing companies have been credited with improving the quality of the service (Athey et al., 2021) and reducing matching frictions (Fréchette et al., 2019) as compared to traditional taxis, they have also contributed to the increase in congestion (Hang et al., 2019; Li et al., 2021; Tarduno, 2021), a serious and growing issue that costs each U.S. driver an average of $1,400 per year accounting for 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 racial groups can lead to a higher pass-through rate of congestion taxes for trips from areas with a higher share of population from minorities, unequally affecting urban mobility capabilities across different racial groups.

The close intersection between housing and transportation is the premise of this issue. In fact, housing segregation, which is still a distinguishing feature of American cities, not only limits racial integration, but also contributes to the disconnect between workers and jobs, possibly affecting minorities' transportation costs, levels of employment, wages and hence overall quality of life.[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 racial integration and reduce spatial mismatches. Hence, congestion taxes can exacerbate racial disparities by unequally affecting urban mobility, thus generating unintended and undesirable long–run negative social effects.[3]

For all these reasons, it is surprising that the potentially unequal consequences of congestion taxes have been largely ignored by policymakers and researchers. The purpose of

[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 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.

this paper is to examine the heterogeneous effects across racial groups of congestion taxes on ride-sharing, focusing on ride-sharing prices and commuting flows as well as rider surplus. I study the case of Chicago since 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 to any other trip. This is the largest tax on ride-sharing in the U.S.. Moreover, Chicago is a very segregated city. Black population is concentrated in the south of the city, Hispanic in the west and White population in the north.[4] These two aspects make Chicago an ideal setting to investigate the differential tax burden on different racial groups.

My approach to studying the impact of the Chicago congestion tax consists of two steps. First, for each community area, I use k-mean clustering to compute thresholds for the percentage of population of any race, above which an area can be defined as predominantly Asian, Black, Hispanic, or White; in this way, I can aggregate community areas into four larger racial areas. Second, I use a "Regression Discontinuity in Time" design that accounts for recurrent seasonal effects at the tax implementation date to estimate the pass-through rates and the change in the total number of trips.[5] 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") from those to any other area of the city.

First, I find that, on average, the price increase was the highest (\$0.972/ride) for trips starting in Black areas, while it was the lowest (\$0.750/ride) for trips starting in White areas, corresponding to tax pass-through rates of 160.30% and 94.98%, respectively. This is consistent with a larger elasticity of demand in White areas due to better access to public transit and wider availability of private vehicles across the population. I explicitly test these potential mechanisms, finding that community areas with better access to public transit and private cars experienced lower pass-through rates. Second, I test whether, within racial

[4] "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.

[5] This approach allows me to exclude from the sample data potentially contaminated by the outbreak of COVID-19. In effect, the most recent date I use in my estimation is February 19, 2020, corresponding to a bandwidth of 34 days. For example, Anderson (2014), who relies on a similar approach, uses 28 days around the cutoff date.

groups, pass-through rates are larger for trips that most likely capture commuting to work, consistently with a more inelastic demand for these rides. I find that this is not always the case possibly because the value of using other transportation means — like for example public transit — is higher during those times. Third, the increase in riders' cost of using ride-sharing significantly reduced the number of ride-sharing trips, particularly from Black and Hispanic areas.[6] Lastly, a simple back of the envelope calculation suggests that riders from Black areas were the most penalized by the tax, with an aggregate loss of over $17,000 per day.

This analysis contributes to the relevant literature and policy discussions in several ways. First, it shows that policies aimed at correcting negative externalities, such as congestion, can have substantial distributional and social effects. In Chicago, the congestion tax penalized Black areas more than others without significantly reducing congestion (Leccese, 2022). Although I focus on ride-sharing taxes, my results mainly rely on the differential access across racial groups to alternatives to the taxed product. This means that the same mechanisms can apply to other similar settings. Moreover, I focus on the interaction of the tax with racial disparities, but the correlation between race and income suggests that relations with income inequality issues are also possible.[7] Second, this paper contributes to the urban economics literature evaluating the impact of transportation policies on urban mobility by showing that taxing ride-sharing trips reduces ride-sharing usage, particularly in Black and Hispanic areas. This suggests that taxes on ride-sharing can increase isolation for some neighborhoods more than for others, although a complete assessment of the impact of the congestion tax on urban mobility would require the investigation of commuters' substitution

[6]Nonetheless, Leccese (2022) finds that the Chicago congestion tax did not significantly reduce congestion in the city. This is because ride-sharing users switched to traditional taxis — particularly for trips to and from the downtown area of the city — and to pooled rides, which are also offered by ride-sharing companies and are not considered in this analysis.

[7]This insight is consistent with the findings of other papers. Donna (2021) shows that gasoline taxes are regressive since low-income consumers are more likely to switch from car to public transit. Moreover, Kãnzig (2021) shows that carbon taxes can negatively affect economic activity, generating a cost which is primarily borne by poorer households. Lastly, Harding et al. (2012) demonstrate that the incidence of cigarette taxes varies not only by household income, but also education, which may also be correlated with race.

patterns to other transportation means.[8] Third, documenting the heterogeneity in shifting patterns across geographic locations is of interest per se and contributes to the literature on the spatial heterogeneity of tax pass-through rates (e.g., Harding et al (2012), and Hindriks and Serse (2019)). While these papers focus on traditional consumption goods (cigarettes and alcohol, respectively), I document heterogeneity in the context of ride-sharing services, which are peer–to–peer marketplaces connecting drivers to riders.[9]

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 how CAs are clustered into the four racial areas considered in this study. Section 4 presents the estimates of pass-through rates. Section 5 proposes possible explanations for the estimated pass-through rates. Section 6 discusses the effect of the tax on riders, 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 private vehicles and public transit (Stiglic et al., 2018; Djavadian et al., 2021). 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%.[10] According the BACP Report,

[8] For Chicago, Leccese (2022) studies the extent to which riders substitute between ride-sharing services and traditional taxis, while Rose (1986) and Donna (2021) focus on the substitution between private cars and public transit.

[9] Wilking (2020) studies 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.

[10] 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`.

this explosive growth is an important factor for the increase in traffic congestion.[11]

Therefore, to reduce congestion and simultaneously raise money for the city budget, Chicago implemented a new congestion tax starting January 6, 2020. In effects, the policy was a tax on ride-sharing as no other transportation mean (public transit, private cars, or traditional taxis) was taxed. The congestion 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 6AM and 10PM starting or ending in a designated surcharge zone, which entirely includes The Loop, while for any other ride the tax amounted to $1.25.[12] The Chicago congestion tax is the highest surcharge faced by TNPs in the US.

Although the congestion tax was motivated by a desire to reduce the negative social effects of traffic congestion (e.g., lost time commuting for residents and increased traffic collisions), TNPs are not their only cause. In fact, other cities implemented congestion pricing regulations that affected other transportation means as well. For example, recently, New York City imposed a surcharge for trips passing through Manhattan if provided by either TNPs or traditional taxis, while in Europe, London and Stockholm imposed taxes on the usage of private vehicles.

Furthermore, Chicago is one of the most racially segregated cities in the U.S., with Black population leaving predominately on the south and west sides, Whites to the north, and Hispanic to the northwest and southwest.[13] 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 popu-

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

[12] 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 6AM and 10PM starting or ending in the designated surcharge zone and to $0.65 for any other trip.

[13] 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.

lation 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.[14]

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

3 Data

In this section, I describe the data I use in my analyses and then explain the approach followed to identify four racial areas within Chicago. Lastly, I summarize how I construct my final sample.

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 date, time, price and endpoints of the ride, as well as other information including length (in miles), duration (in seconds), tolls, taxes, tip and an identifier for whether the ride was shared (i.e., two or more riders booked separately and shared the ride) 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

[14]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.

also use this dataset to construct a control variable for my regression analysis.

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 races (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 pass-through.

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, snow fall, temperature and a dummy for whether there was thunder or not are provided.

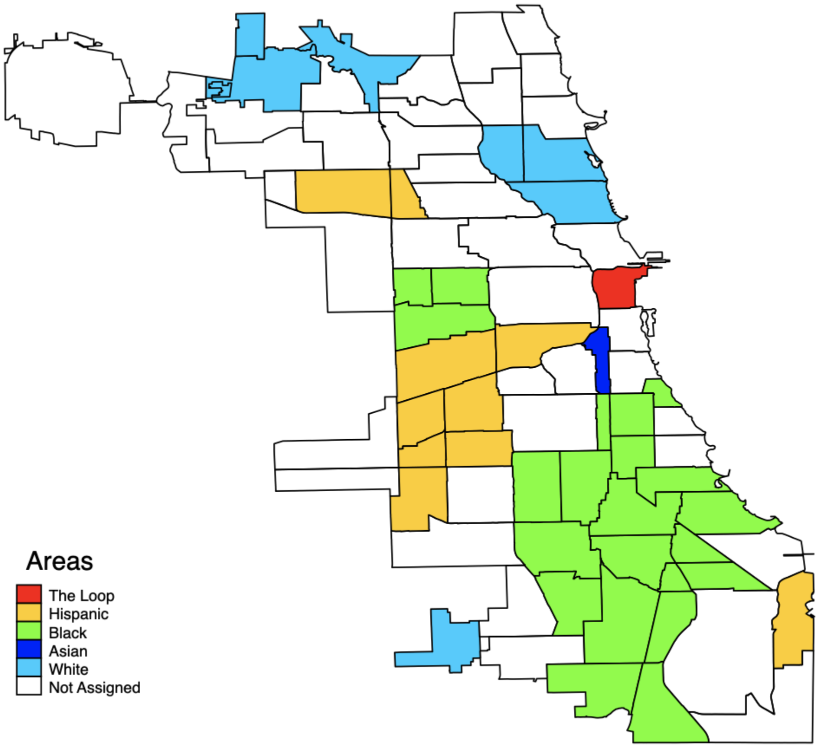
3.2 Identification of Racial Areas

Using data on the percentage of Asian, Black, Hispanic and White population residing in each CA, I use k-mean clustering to define thresholds for the percentage of population of any race above which the CA can be identified as Asian, Black, Hispanic or White.[15]

The threshold identified by the algorithm are relatively large (72.28% for the Asian area, 82.93% for the Black area, 74.93% for the Hispanic area, and 69.49% for the White area), which is emblematic of the high level of housing segregation in Chicago, but also ensures a clean identification of racial areas. This approach assigns every CA to one of the four races or no race, if there is no predominant race in the CA.

[15] Figures B.5, B.6, B.7, B.8 in the Appendix illustrate the results of the k-mean clustering algorithm for each race. I define a CA to be predominantly of a race if the percentage of population of that race is above the race-specific largest threshold identified by the algorithm. For example, Figures B.6 shows that any CA where more than the 82.9313% of the population is Black is part of the Black area.

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). The four racial areas are identified through k-mean clustering, while The Loop is the CA number 32. Any other area in which there is no predominant race is left in white.

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 the Metro Area, housing a large number of City, County, and State government workers.[16]

In this way, I can divide Chicago in four major racial areas, and The Loop. 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.

[16]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`.

3.3 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 congestion tax, I focus on week-day trips starting after 6AM and ending before 10PM, and I drop holidays from the sample.[17] Moreover, I drop observations that have unreasonable prices or distances, which are probably the consequence of reporting errors.

I consider different types of rides based on geographical endpoints and time, partly to account for the different tax amounts levied by the city. First, since I am interested in quantifying the burden of the tax falling on each racial group, I distinguish trips starting from any of the four racial areas identified (Asian, Black, Hispanic and White). This means that trips starting in CAs that do not belong to any of the four racial areas — i.e., CAs in white in Figure 1 — are excluded from the analysis.[18] Second, I distinguish trips to The Loop from trips to any other destination due to its strategic importance and the higher tax amount trips to the Loop are subject to.[19] Third, I use the time of the ride to distinguish trips based on their purpose. I assume that trips between 6AM and 10AM are for work reasons and I call them "work" or "work-time" trips, while I refer to any other trip as "leisure" or "leisure-time" trips. Therefore, overall I define sixteen different types of rides based on the area from which the trip starts (Asian, Black, Hispanic, White), the area in which it ends (The loop, or any other area), and the time/purpose of the ride (work, or leisure).

Lastly, my sample focuses on the period around the implementation of the congestion tax, i.e., January 6, 2020. I consider different intervals of days around the cutoff date, the longest being 34 days, which implies that the most recent calendar date in the sample is

[17]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.

[18]The Near North Side borders the Loop to the north and is partially included into the surcharge zone designated by the city. Since I cannot identify the exact tax amount levied on some of the trips starting in this area, I exclude this CA from the White Area (i.e., this CA is colored in white in Figure 1). On the other hand, O'Hare is the CA where the main airport of the city is located. To avoid contamination, I exclude this CA from the White area as well.

[19]Since the designated surcharge zone straddles the Near North Side and the Near West Side, I cannot identify the tax amount levied on trips starting from any of the four racial areas and ending in these two CAs. Thus, I exclude such trips from the analyses.

February 20, 2020. In this way, I avoid any contamination following the outbreak of COVID-19.[20] 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 congestion 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.

4 The Heterogeneous Pass-through of the Congestion Tax

I begin by examining the impact of the congestion tax on the price per ride of ride-sharing. My identification strategy exploits the exogenous variation provided by the implementation of the tax on January 6, 2020 to compare prices before and after this cutoff date. However, since the policy started on the first Monday after a period of holidays, during which activities normally slow down, to isolate the effect of the ride-sharing tax on prices from recurrent seasonal effects at the cutoff date I follow Leccese (2022). This approach "deducts" the change in prices occurred after a hypothetical tax implementation date, which is defined as the first Monday after the same period of holidays in the previous year, i.e., January 7, 2019, from the change in prices following the beginning of the congestion tax.[21]

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 include in the regression model a dummy equal to one if the observation is after this hypothetical policy date, or after the actual implementation date of the congestion tax.[22] In particular, for each type of ride (e.g., starting in the Hispanic area

[20] 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.

[21] 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 congestion tax. However, this is not feasible in my setting because data on TNP trips are only available since November 2018.

[22] To make the two subsamples comparable, I construct them so that the number of times each day of the

during work-time and ending in The Loop), I estimate the following baseline equation for trip o occurring on day t:

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

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

where p_{ot} is the price of trip o occurred in day t starting in any of the four racial areas identified, ending within or outside the Loop, and happening during work- or leisure-time; $Y20_t$ ($Y19_t$) 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 equal to 1 after January 7, 2019 or after January 6, 2020 (included) which controls for the seasonal change in prices around the cutoff date; $\boldsymbol{\delta_t}$ are time fixed effects, which include dummies for days of the week, weeks of the year and months; $\boldsymbol{X_t}$ is a matrix of control variables which includes the length of the trip in miles, the amount of precipitations, wind speed, snow fall, temperature and a dummy for whether there was a thunder. Hence, ($\mathbb{1}\{D_t \geq 0\} \cdot Y20_t$) is equal to 1 on or after the beginning of the congestion tax (January 6, 2020), and 0 otherwise, and β represents the coefficient of interest, capturing the effect of the congestion 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 week days in Sample 18-19 and Sample 19-20, and this makes it

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.

difficult to line up the two sets of dates perfectly across the two subsamples. This generalizes the local linear models used in the Regression Discontinuity in Time (RDiT) literature (e.g., Imbens and Lemiux (2008), Anderson (2014)) 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.[23]

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.

Table 1 summarizes the estimated effect of the congestion tax on prices, as well as the implied pass-through. In the top panel, columns (1)–(4) refer to work trips to The Loop starting in any of the for 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 for racial areas, while columns (5)–(8) to leisure trips to any CA excluding The Loop 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 for work starting in the Asian area and ending outside The Loop, and such increases were very heterogeneous across types of rides.[24] 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 for a trip to the Loop ranged between \$1.83 and \$2.47, while the range was \$0-\$1.18 for any other trip. For example, the price of a work-trip starting in the Hispanic area and ending outside The Loop increased on average by \$0.66 — which

[23] Klein et al. (2022) use a similar approach to study patients' response to dynamic incentives in health insurance contracts with deductibles, and label the approach "Differences-in-Regression-Discontinuities".

[24] I formally verify that for each type of ride the changes in price were heterogeneous across racial areas by performing statistical tests of equality between the estimated coefficients βs for different racial groups. The results of these tests are reported in Table A.7, and in most cases confirm the existence of significant differences in price changes.

Table 1: Estimated price changes and pass-through rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trips to the Loop								
	WORK				LEISURE			
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
β	1.827***	2.474***	2.011***	2.044***	2.333***	2.394***	2.322***	1.985***
	(0.184)	(0.0863)	(0.0726)	(0.0473)	(0.100)	(0.0802)	(0.0717)	(0.0415)
Pass-through	80.132%	108.509%	88.202%	89.649%	102.193%	105.000%	101.842%	87.061%
Observations	3,276	33,857	34,234	180,130	11,159	36,099	31,357	135,481
R-squared	0.496	0.666	0.780	0.321	0.516	0.672	0.785	0.455
Other Rides								
β	0.218	0.878***	0.660***	0.443***	1.182***	0.866***	0.865***	0.524***
	(0.277)	(0.0254)	(0.0373)	(0.0605)	(0.106)	(0.0170)	(0.0227)	(0.0144)
Pass-through	0%	165.660%	124.538%	83.585%	223.019%	163.396%	163.208%	98.679%
Observations	7,105	292,758	162,161	300,329	32,242	704,903	381,498	1,362,982
R-squared	0.869	0.890	0.876	0.785	0.872	0.890	0.885	0.858

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

Notes: β is the effect of the congestion tax on prices ($ per ride), while "Pass-through" is the estimated tax pass-through rate. 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.

corresponds to a 4.93% increase. A similar trip to The Loop experienced an average increase of $2.01, corresponding to a 13.22% increase.[25]

Given the estimates for β, I can compute the tax pass-through rate for different types of rides as the percentage change in the price caused by the tax, divided by the percentage increase in the tax amount charged. The observed heterogeneity in price increases directly translates into heterogeneous pass-through rates. Most of this heterogeneity is captured by the destination point, with trips to The Loop, in general, displaying lower pass-through rates. However, pass-through rates also differ across time-windows. In this regard, one might expect work-trips to experience higher pass-through than leisure-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 pass-through of 88.20% if taken during work-time, while pass-through for a similar leisure-ride was 101.84%. A possible explanation for these findings could be that some alternative transportation means — e.g., public transit — function more efficiently during work-times, thus making demand for ride-sharing from some CAs more elastic.

Remarkably, residents of Black areas were the only ones experiencing pass-through rates above 100% on all types of rides — ranging from 105% for leisure-rides to The Loop to more than 165% for work-rides to CAs outside The Loop. In contrast, trips starting in White areas tended to have lower pass-through rates, ranging between 83.59% and 98.68%. Taking the average across racial areas weighted by the number of rides of each type makes this gap even more striking: indeed, on average, the tax pass-through rate was the 160.30% for trips starting in Black areas, while it was 94.98% for trips starting in White areas. It is noteworthy that pass-through rates are sometimes 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), Leccese (2022) argues that in the ride-sharing market the existence of

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

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., single and pooled rides) make it easier to rationalize tax overshifting than in a traditional one-sided market with single-product firms.

In my 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 (e.g., 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.3 and A.4 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 specification including CAs of origin and destination fixed effects. This allows to control for 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.2 and are consistent with the results in Table 1, showing that in practice all these potential concerns do not affect the results of the main specification considered.

My results show that the congestion tax affected Chicago CAs heterogeneously, and Black areas experienced largest price increases. Moreover, since changes in the cost of transportation can affect the spatial organization of cities (Bryan et al., 2020; Tsivanidis, 2018), the congestion tax may exacerbate racial segregation in the long-run. Lastly, the correlation between race and median income — which is illustrated in Figure B.2 of the Appendix —

suggests that the tax may as well have long-run effects on income segregation.[26]

5 Possible Drivers of the Heterogeneity in Pass-through

A natural policy-related question is what drives higher pass-through rates for trips starting in some 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 pass-through rates.

I consider two mechanisms. First, CAs in which residents have better access to substitute transportation means should experience lower pass-through rates. Thus, if public transit and private cars are substitute of ride-sharing, then CAs with better access to public transit or where residents are more likely to own a car should experience lower pass-through rates. A similar argument may as well apply to traditional taxis and shared TNP services. However, in these cases an additional channel may be at play. Indeed, the fact that residents of a CA rely more heavily on these services, which are arguably closer in nature to single ride-sharing rides, may reveal a stronger preference of residents towards "for-hire vehcles." These could lead to a less elastic demand for single ride-sharing trips in CAs where people use taxi and shared TNP services more, and hence to a positive correlation between usage of these two alternatives and tax pass-through rates.

Effectively, I first use the same model presented in Equation 1 to estimate the pass-through rate for trips to The Loop and to any other area, separately.[27] However, I do not distinguish work- from leisure-times and I do not aggregate CAs into racial areas, but I estimate CA-level pass-through rates based on the starting CA of the ride. 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

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

[27]As in the previous analyses, I drop trips ending in the Near North Side and in the Near West Side because I cannot perfectly identify the tax amount levied on these rides.

the analysis trips having it as the starting CA. In addition, I drop trips starting in the Near North Side or in the Near West Side because I cannot perfectly identify the tax amount levied on these rides.

Next, I run a regression at the CA-level, where I regress the estimated CA-level pass-through rate on several covariates, which reflect the availability of alternative means of transportation in the CA. First, access to public transit is proxied by the number of LTrain stops per square mile located in the CA ("LTrain stops"). Second, I measure availability of private cars as the percentage of households residing in the CA with at least one private car ("Private cars"). Third, I consider traditional taxi service usage, as well as usage of shared ride-sharing services. I measure the former as the natural log of the average number of daily taxi trips starting from the CA in any weekday of November and December 2019 ("Taxi service usage"), and the latter as the natural log of the average number of daily shared TNP trips starting from the CA in any weekday of November and December 2019 ("Shared service usage"). Lastly, in all regressions I control for the presence of an airport in the CA, which is the case for two CAs (i.e., O'Hare and Clearing).

Table 2 reports the results of these regressions, and covariates' signs are as expected. In Column (1) the dependent variable is the estimated pass-through rate for trips starting in any CA and ending in The Loop. I find that a marginal increase in the average availability of private cars in a CA is correlated with almost a 1% decrease in the tax pass-through rate. Moreover, a 1% increase in the usage of shared TNP services correlates with a 0.28% higher pass-through rate. Thus, in both cases the magnitude of the correlation is relative low.

Column (2) shows the results of a similar regression in which pass-through rates refer to trips ending outside The Loop. I find that the availability of private vehicles does not significantly impact pass-through rates for trips to CAs outside The Loop. In contrast, access to public transit seem to play a crucial role being the main driver of pass-through: a marginal increase in the number of Ltrain stops per square mile in a CA is related to a 18% lower pass-through rate. This suggests that ride-sharing is primarily in competition with public transit to connect riders to areas outside the Loop. Finally, a 1% increase in the

Table 2: Correlation between estimated CA-level pass-through rates and community area's characteristics

VARIABLES	(1) Loop	(2) Other
LTrain stops	-5.492	-18.06**
	(6.095)	(8.770)
Private cars	-0.967**	-0.984*
	(0.443)	(0.584)
Taxi service usage	0.0701	0.0118
	(0.0482)	(0.114)
Shared service usage	0.277**	-0.468***
	(0.112)	(0.157)
Observations	74	74
R-squared	0.121	0.159

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

Notes: The table shows results for the regression of CA-level estimated pass-through rate on several covariates. In Column (1) the dependent variable is the estimated pass-through rate for trips starting in any CA (except the Loop, the Near North Side and the Near West Side) and ending in The Loop. In Column (2) estimated pass-through rates refer to similar trips ending outside The Loop (but not in the Near North Side or the Near West Side). Thus, the relevant unit is a cross-section of CAs. The covariates I consider include: 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, 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 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. In both regressions I control for the presence of an airport in the CA (this is the case for two CAs, i.e., O'Hare and Clearing). Robust standard errors are reported in parentheses.

usage of shared TNPs is correlated with a 0.47% lower pass-through rate.

My results are consistent with the fact that the heterogeneity in pass-through rates across racial groups may be driven by differences in demand elasticities. These, in turn, depend on the competition between alternative transportation means in each CA. In fact, as compared to residents of predominantly White CAs, residents of predominantly Black areas are more likely to have no access to private cars and have worst access to the Ltrain.[28] This can explain the higher pass-through rates observed in Black areas.

6 The Impact of the Congestion Tax on Riders

Learning how different racial groups respond to changes in the cost of using ride-sharing can provide key insights into their underlying demand and help guide future policies.[29] Thus, I next examine riders' response to the increase in prices following the tax and quantify the welfare impact of the congestion tax on riders.

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 congestion tax on the dependent variable — β_q to ease exposition.[30] 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 3 reports estimates of β_q for different types of rides. In the top panel, columns (1)–(4) refer to work-trips to The Loop starting from Asian, Black and White areas, respectively, while columns (5)–(8) refer 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

[28] The former is illustrated in panel (b) of Figure B.3 in the Appendix. The latter is illustrated in Figure B.4 of the Appendix, and it is also consistent with the fact that, as displayed in panel (a) of Figure B.3 in the Appendix, the percentage of commuters using public transit is the highest in predominantly White CAs.

[29] This applies to any group of users identifiable (e.g., via race, like in this paper, 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 fell more unsafe using public transit.

[30] 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.

Table 3: Effects of the tax on the number of rides

	Rides to the Loop							
	WORK				LEISURE			
	(1) Asian	(2) Black	(3) Hispanic	(4) White	(5) Asian	(6) Black	(7) Hispanic	(8) White
β_q	-0.184	-0.172***	-0.151**	-0.127	0.0116	-0.184***	-0.110**	-0.0158
	(0.148)	(0.0651)	(0.0744)	(0.0773)	(0.108)	(0.0404)	(0.0489)	(0.0408)
Observations	116	116	116	116	116	116	116	116
R-squared	0.478	0.820	0.755	0.792	0.698	0.837	0.824	0.848
	Other Rides							
β_q	-0.0381	-0.126*	-0.102**	-0.0592	-0.0195	-0.123***	-0.0876***	-0.0701
	(0.104)	(0.0671)	(0.0486)	(0.0391)	(0.0802)	(0.0299)	(0.0309)	(0.0506)
Observations	116	116	116	116	116	116	116	116
R-squared	0.797	0.823	0.888	0.827	0.813	0.951	0.955	0.910

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

Notes: The table reports coefficients estimating the effect of the congestion 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.

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. Robust standard errors are reported in parentheses.

Table 3 shows that there was no significant reduction in the number of trips starting in Asian and White areas, which can be explained by the lower price increase experienced by these rides. In contrast, there was a reduction in the equilibrium number of trips from Black and Hispanic areas, except for work-rides starting in the Black area and ending outside The Loop. Concerning work-trips to The Loop, riders picked-up in Black and Hispanic areas responded in a similar way: the price increase for Black riders was \$0.46 larger, and their equilibrium number of rides indeed decreased more (by 15.80%, as compared to the 14.02% reduction of that of Hispanic riders).[31] Results are different for leisure-trips, where

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

Table 4: Estimated loss in RS across racial areas

	(1) Asian	(2) Black	(3) Hispanic	(4) White
Loss in RS ($ per day)	949.10	17,310.12	9,200.69	10,396.16
Loss in RS per-commuter ($ per 30 weekdays)	7.12	3.77	2.12	2.33

Notes: The Loss in RS is calculated using Equation 2. To compute the loss in RS per-commuter, since the data do not provide the number of unique riders across racial groups, I assume that the pool of potential riders is approximated by the the number of people who commute to work in each community area, and I assign commuters to racial groups proportionally using the percentage of each group in the entire community area population.

the difference in estimated price changes between trips from Black and Hispanic area was negligible (i.e., $0.07 for trips to the Loop, and no difference for the others), but riders picked-up in the Black area reduced ride-sharing usage significantly more than those picked-up in the Hispanic area. In particular, I find that the reductions in the equilibrium number of rides to The Loop were 16.81% and 10.42% for trips from Black and Hispanic areas, respectively, while for trips ending outside The Loop reductions amounted to 11.57% and 8.39%, respectively.

Furthermore, since pass-through is a sufficient statistic for various welfare analyses (Chetty, 2009), I can use estimates of Table 1 to quantify the loss in riders' surplus (RS). While simple and intuitive, a caveat of this approach is that it abstracts from the role of specific features of the ride-sharing market—such as waiting times—that may however matter for welfare.[32] Thus, rather than to perform a complete welfare analysis—which would require a detailed structural model—, the main goal of this exercise is to develop a rough understanding of the potential heterogeneous welfare consequences of congestion taxes on ride-sharing for riders of different racial groups.

[32] For example, Castillo (2020) argues that ride-sharing markets clear through a hybrid mechanism involving both the surge pricing algorithm and waiting times. This matters for welfare because, theoretically, one can construct examples in which a higher price leads to reductions in waiting times that, in net, can increase RS.

Applying incidence formulas in Weyl and Fabinger (2013) to my setting, I can write:

$$\text{Loss in RS} = -|\hat{\rho}_j^{loop} \times q_j^{loop} + \hat{\rho}_j^{other} \times q_j^{other}|, \tag{2}$$

where $\hat{\rho}_j^k$ is the estimated pass-through rate for trips from area j to area k, where k in my framework is either The Loop ("*loop*") or any other CA ("*other*"). The first row of Table 4 shows that riders commuting from Black areas were the most penalized by the tax, with an aggregate loss of over $17,000 per day. Losses were lower in the other areas: $949.10 for the Asian area, $9,200.69 for the Hispanic area and $10,396.16 for the White area. These estimates refer to the total cost of the congestion tax borne by each racial area, but they are affected by the size of each area. In effect, as shown in Figure 1, the Black area includes more CAs than the Hispanic and the White area, and these are, in turn, bigger than the Asian area, which only includes one CA.

To address this issue, I consider the loss in RS per-rider in each racial area. Since the data do not provide the number of unique riders in each CA, I assume that the pool of potential riders is approximated by the number of people who commute to work — which is available in CMAP data — and I assign commuters to racial groups proportionally using the percentage of each group in the entire CA population. I find that even controlling for the size of the racial area, a rider commuting from the Black area was hit by the congestion tax more severely than one commuting from Hispanic or White areas, with a loss of almost $4 per 30 week-days, as compared to losses just above $2 for riders commuting from Hispanic or White areas. Instead, the loss in RS per-commuter for the Asian area ($7.12 per 30 weekdays) was larger than that for the Black area, even if estimates for the Asian area only rely on one CA (i.e., Armour Square) and hence need to be interpreted with more caution.

Finally, although estimates of the loss in RS per-commuter may appear to be small, they need to be interpreted as lower bounds because to normalize the loss in RS I use the number of commuters in each CA using any transportation mean, which is much larger than the actual number of ride-sharing users — i.e., the factor that should have been ideally used, but it is not available in my data.[33]

7 Conclusion

Combining data from multiple sources, I show that the effects of the Chicago congestion tax, which was only levied on ride-sharing trips, were heterogeneous across racial groups, hitting particularly severely CAs where the population is predominantly Black. In particular, I find that: (1) on average, the tax pass-through rate was the highest (160.30%) for trips starting in Black areas, while it was the lowest (94.98%) for trips starting in White areas; (2) the availability of alternative transportation options is an important driver for the observed heterogeneity in pass-through rates across CAs; (3) the increase in riders' cost of using ride-sharing significantly reduced the number of ride-sharing trips, particularly from Black and Hispanic areas; (4) riders commuting from Black areas were the most penalized by the tax, with an aggregate loss of over $17,000 per day.

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 Black CAs more than others, and at the same time failed to reduce congestion (Leccese, 2022). The asymmetric reduction in the usage of ride-sharing across racial areas found in this paper also suggests the existence of additional long-term costs associated with congestion pricing 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.

[33] By construction, the non-normalized estimates of the loss in RS do not suffer from this issue.

References

Acs, Gregory, Rolf Pendall, Mark Treskon, and Amy Khare. 2017. "The cost of segregation." *Washington, DC: Urban Institute.*

Anderson, Michael L. 2014. "Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion." *American Economic Review*, 104(9): 2763–96.

Athey, Susan, Juan Camilo Castillo, and Bharat Chandar. 2021. "Service Quality on Online Platforms: Empirical Evidence about Driving Quality at Uber." SSRN Working Paper 3499781.

Bailey, Michael, Patrick Farrell, Theresa Kuchler, and Johannes Stroebel. 2020. "Social connectedness in urban areas." *Journal of Urban Economics*, 118: 103264.

Breymaier, Rob, Morgan Davis, and Patricia Fron. 2013. "Fair Housing and Equity Assessment: Metropolitan Chicago." *Chicago Metropolitan Agency for Planning and Chicago Area Fair Housing Alliance. Available at http://www. cmap. illinois. gov/livability/housing/fair-housing.*

Bryan, Gharad, Edward Glaeser, and Nick Tsivanidis. 2020. "Cities in the Developing World." *Annual Review of Economics*, 12: 273–297.

Christensen, Peter, and Adam Osman. 2021. "The Demand for Mobility: Evidence from an Experiment with Uber Riders." IZA Discussion Paper 14179.

Djavadian, Shadi, Bilal Farooq, and Seyed Mehdi Meshkani. 2021. "Demand for Shared Mobility to Complement Public Transportation: Human Driven and Autonomous Vehicles."

Donna, Javier D.. 2021. "Measuring Long-Run Gasoline Price Elasticities in Urban Travel Demand." SSRN Working Paper 3285200.

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

Hang, Chengzheng, Zhenfei Liu, Yujing Wang, Caiyi Hu, Yuelong Su, and Zhenning Dong. 2019. "Sharing diseconomy: impact of the subsidy war of ride-sharing companies on urban congestion." *International Journal of Logistics Research and Applications*, 22(5): 491–500.

Harding, Matthew, Ephraim Leibtag, and Michael F Lovenheim. 2012. "The heterogeneous geographic and socioeconomic incidence of cigarette taxes: evidence from Nielsen homescan data." *American Economic Journal: Economic Policy*, 4(4): 169–98.

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

Imbens, Guido W., and Thomas Lemieux. 2008. "Regression discontinuity designs: A guide to practice." *Journal of Econometrics*, 142(2): 615–635.

Kain, John F. 1968. "Housing segregation, negro employment, and metropolitan decentralization." *The quarterly journal of economics*, 82(2): 175–197.

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

Kãnzig, Diego R. 2021. "The Unequal Economic Consequences of Carbon Pricing." SSRN Working Paper 3786030.

Leccese, Mario. 2022. "Asymmetric Taxation, Pass-through and Market Competition: Evidence from Ride-sharing and Taxis." SSRN Working Paper 3824453.

Li, Ziru, Chen Liang, Yili Hong, and Zhongju Zhang. 2021. "How Do On-demand Ridesharing Services Affect Traffic Congestion? The Moderating Role of Urban Compactness." SSRN Working Paper 2838043.

Rose, Geoffrey. 1986. "Transit passenger response: short and long term elasticities using time series analysis." *Transportation*, 13(2): 131–141.

Stiglic, Mitja, Niels Agatz, Martin Savelsbergh, and Mirko Gradisar. 2018. "Enhancing urban mobility: Integrating ride-sharing and public transit." *Computers & Operations Research*, 90: 12–21.

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

Tsivanidis, John Nicholas. 2018. "The Aggregate and Distributional Effects of Urban Transit Infrastructure: Evidence from Bogotá's Transmilenio." University of Chicago Working Paper.

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

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

Appendix A Additional Tables

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

	Rides to the Loop		Other Rides	
	Work	Leisure	Work	Leisure
Price from Asian area	11.59	10.54	14.60	13.86
Price from Black area	18.59	17.22	13.72	13.19
Price from Hispanic area	15.21	14.72	13.39	13.22
Price from White area	14.76	14.45	17.73	12.25
Price/mi from Asian area	3.47	3.85	4.84	4.41
Price/mi from Black area	2.24	2.16	3.90	3.66
Price/mi from Hispanic area	2.91	2.83	3.92	3.98
Price/mi from White area	2.91	2.84	4.03	4.66
ln(# of rides from Asian area)	3.43	4.78	4.33	5.81
ln(# of rides from Black area)	5.87	5.91	7.96	8.87
ln(# of rides from Hispanic area)	5.85	5.77	7.40	8.28
ln(# of rides from White area)	7.32	7.17	7.87	9.44

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 congestion tax, excluding holidays.

Table A.2: Estimated effect on prices including CA origin and destination fixed effects

	Trips to the Loop							
	WORK				LEISURE			
	(1) Asian	(2) Black	(3) Hispanic	(4) White	(5) Asian	(6) Black	(7) Hispanic	(8) White
β	1.827***	2.474***	1.993***	2.037***	2.333***	2.415***	2.371***	1.980***
	(0.211)	(0.117)	(0.140)	(0.227)	(0.133)	(0.092)	(0.090)	(0.107)
Observations	3,276	33,857	34,234	180,130	11,159	36,099	31,357	135,481
R-squared	0.496	0.675	0.794	0.325	0.516	0.691	0.804	0.465
	Other Rides							
β	0.580**	0.884***	0.681***	0.406**	0.968***	0.854***	0.864***	0.558***
	(0.266)	(0.028)	(0.047)	(0.196)	(0.130)	(0.022)	(0.031)	(0.045)
Observations	6,511	268,214	142,504	274,205	30,329	644,768	334,786	1,302,485
R-squared	0.872	0.888	0.881	0.818	0.862	0.889	0.885	0.881

Robust 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 1. 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.3: Estimated effects of the congestion tax on TNP price per trip with a longer bandwidth

	Rides to the Loop							
	WORK				LEISURE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
β	1.564***	2.084***	1.739***	1.727***	2.351***	2.389***	2.262***	1.946***
	(0.179)	(0.0805)	(0.0681)	(0.0443)	(0.0935)	(0.0711)	(0.0669)	(0.0386)
Observations	3,821	39,874	40,339	209,978	13,122	42,805	37,088	159,276
R-squared	0.491	0.661	0.777	0.319	0.520	0.666	0.781	0.451
	Other Rides							
β	-0.157	0.673***	0.436***	0.0295	1.058***	0.851***	0.830***	0.504***
	(0.254)	(0.0245)	(0.0346)	(0.0579)	(0.0979)	(0.0159)	(0.0212)	(0.0134)
Observations	8,344	344,324	190,948	354,700	38,189	829,270	449,069	1,606,302
R-squared	0.867	0.889	0.877	0.785	0.870	0.889	0.884	0.857

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

Notes: β is the effect of the congestion 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.4: Estimated effects of the congestion tax on TNP price per trip with a shorter bandwidth

	Rides to the Loop							
	WORK				LEISURE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
β	1.699***	2.451***	2.052***	1.992***	2.334***	2.540***	2.316***	1.994***
	(0.201)	(0.0946)	(0.0793)	(0.0527)	(0.111)	(0.0824)	(0.0800)	(0.0453)
Observations	2,659	27,751	28,068	149,507	9,290	29,359	25,561	111,306
R-squared	0.493	0.676	0.789	0.336	0.532	0.699	0.791	0.459
	Other Rides							
β	0.300	0.820***	0.641***	0.533***	1.309***	0.869***	0.900***	0.520***
	(0.330)	(0.0281)	(0.0420)	(0.0680)	(0.115)	(0.0186)	(0.0251)	(0.0159)
Observations	5,669	239,759	132,463	245,796	26,534	577,317	312,092	1,114,629
R-squared	0.878	0.891	0.877	0.790	0.875	0.891	0.885	0.857

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

Notes: β is the effect of the congestion 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 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.5: Effect on the number of rides with a longer bandwidth

	Rides to the Loop							
	WORK				LEISURE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian	Black	Hispanic	White	Asian	Black	Hispanic	White
β_q	-0.167	-0.165**	-0.134*	-0.106	0.0160	-0.209***	-0.0986**	-0.0249
	(0.138)	(0.0634)	(0.0722)	(0.0746)	(0.105)	(0.0403)	(0.0469)	(0.0372)
Observations	136	136	136	136	136	136	136	136
R-squared	0.462	0.822	0.763	0.784	0.703	0.818	0.820	0.854
	Other Rides							
β_q	-0.0103	-0.147**	-0.118**	-0.0614*	-0.0474	-0.127***	-0.0981***	-0.0625
	(0.0950)	(0.0666)	(0.0473)	(0.0368)	(0.0741)	(0.0278)	(0.0280)	(0.0461)
Observations	136	136	136	136	136	136	136	136
R-squared	0.759	0.810	0.885	0.830	0.824	0.949	0.957	0.922

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

Notes: The table reports coefficients estimating the effect of the congestion 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.6: Effect on the number of rides with a shorter bandwidth

	Rides to the Loop							
	WORK				LEISURE			
	(1) Asian	(2) Black	(3) Hispanic	(4) White	(5) Asian	(6) Black	(7) Hispanic	(8) White
β_q	-0.130	-0.146**	-0.154**	-0.103	0.0370	-0.145***	-0.111*	-0.0286
	(0.171)	(0.0644)	(0.0754)	(0.0777)	(0.110)	(0.0495)	(0.0605)	(0.0511)
Observations	96	96	96	96	96	96	96	96
R-squared	0.494	0.841	0.769	0.805	0.669	0.824	0.805	0.845
	Other Rides							
β_q	-0.104	-0.0987	-0.0710	-0.0382	-7.40e-05	-0.0826***	-0.0544	-0.0459
	(0.109)	(0.0710)	(0.0521)	(0.0438)	(0.0892)	(0.0302)	(0.0330)	(0.0575)
Observations	96	96	96	96	96	96	96	96
R-squared	0.808	0.832	0.885	0.839	0.794	0.947	0.950	0.897

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

Notes: The table reports coefficients estimating the effect of the congestion 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 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.

Table A.7: Wald test for the difference in the estimated coefficients for the effect of the Tax on prices across racial areas

HYPOTHESIS TESTED	Rides to the Loop for Work	Rides to the Loop for Leisure	Other rides for Work	Other rides for Leisure
$\beta^{Asian} = \beta^{Black}$	0.001***	0.634	0.017**	0.003***
$\beta^{Asian} = \beta^{Hispanic}$	0.349	0.931	0.113	0.003***
$\beta^{Asian} = \beta^{White}$	0.250	0.001***	0.426	0.000***
$\beta^{Black} = \beta^{Hispanic}$	0.000***	0.505	0.000***	0.979
$\beta^{Black} = \beta^{White}$	0.000***	0.000***	0.000**	0.000***
$\beta^{Hispanic} = \beta^{White}$	0.701	0.000***	0.002***	0.000***

*** p<0.01, ** p<0.05, * p<0.1

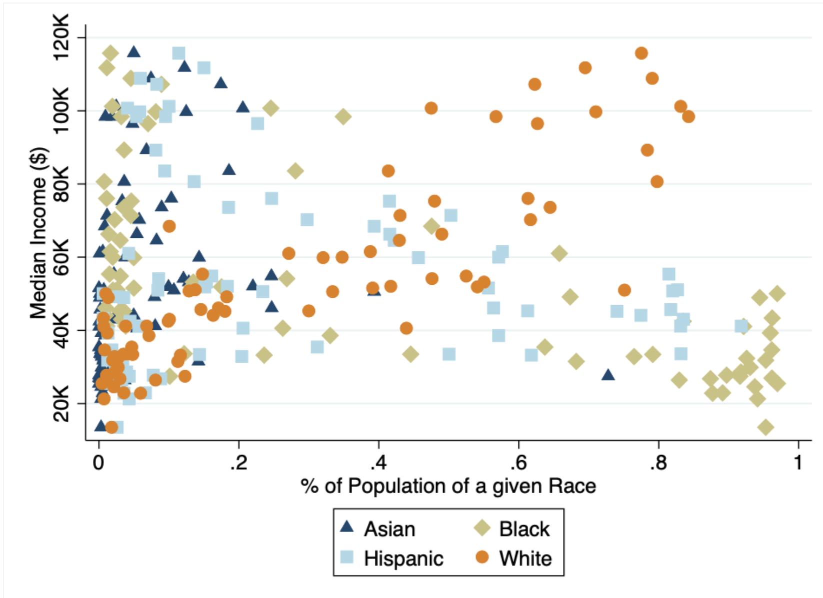
Notes: The table reports the p-values (p) of the Wald Test (i.e., Pr $> \chi^2(1)$) for the equality between the coefficients β for different racial groups estimated in the specifications considered in Table 1.

Appendix B Additional Figures

Figure B.1: Congestion tax surcharge zone

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

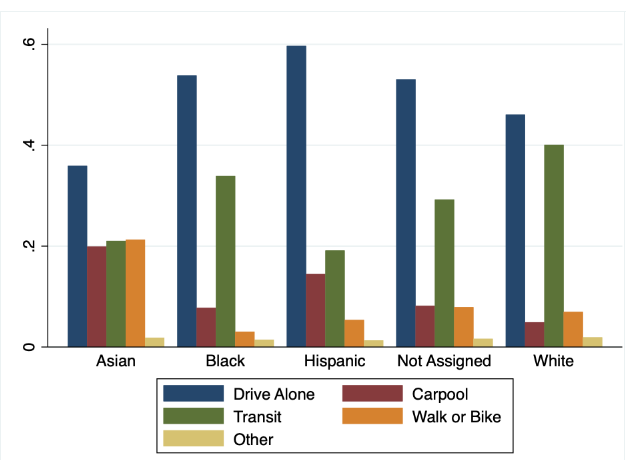
Figure B.2: Median income and race



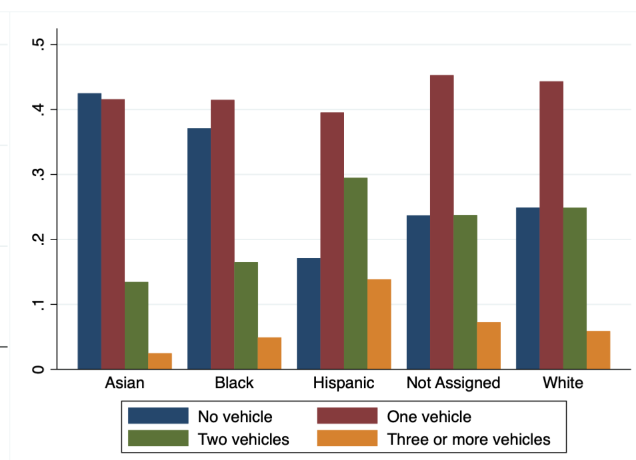
Notes: For each racial group considered, the figure illustrates the correlation between the median income in the CA and the percentage of population of a given race (Asian, Black, Hispanic or White) in that CA.

Figure B.3: Modes of transportation and private vehicles across racial groups

(a) Modes of transportation

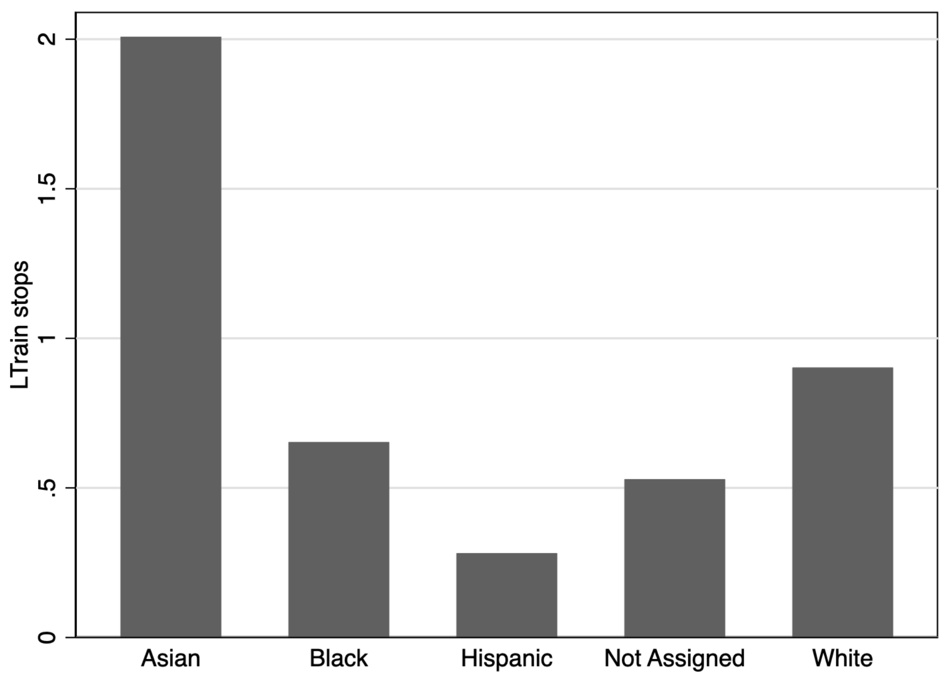


(b) Availability of private vehicles



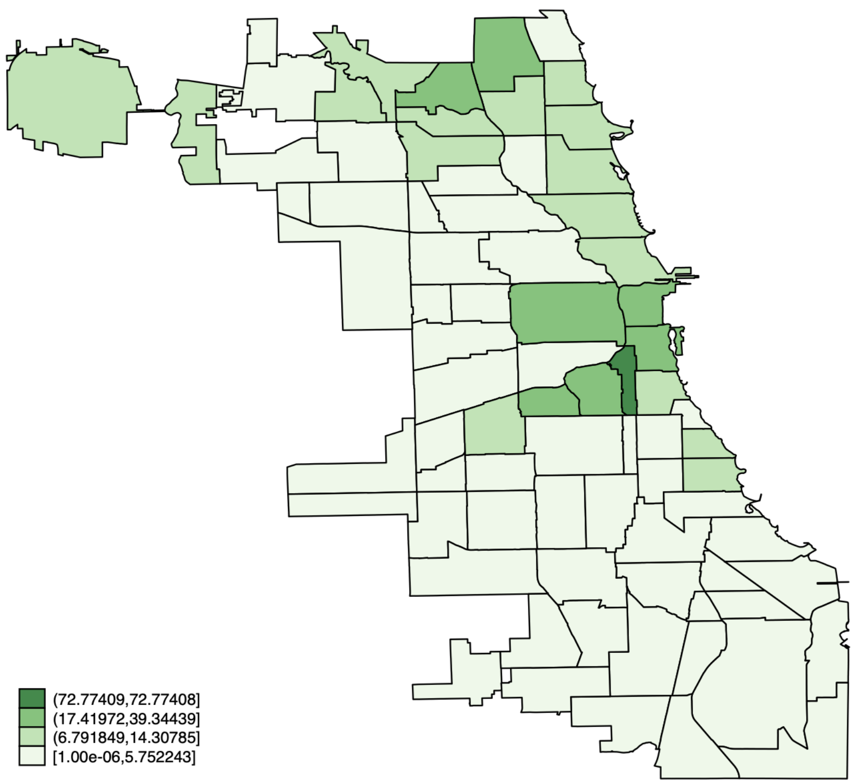
Notes: Panel (a) displays the percentage of commuters using different modes of transportation (Drive Alone, Carpool, (Public) Transit, Walk or Bike, Other) in CAs across the different racial areas identified. Panel (b) shows the percentage of households with 0, 1, 2, and 3 or more private vehicles available in CAs across the different racial areas identified.

Figure B.4: Access to the LTrain across racial areas



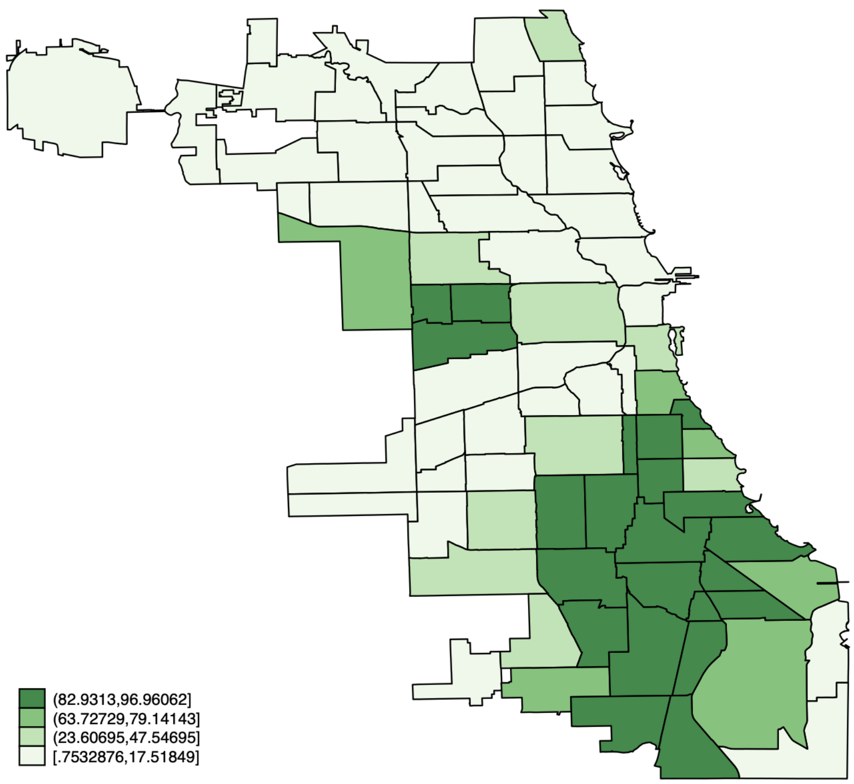
Notes: The figure shows the average number of Ltrain stations per square mile in CAs across the different racial areas identified.

Figure B.5: Distribution of Asian population in Chicago



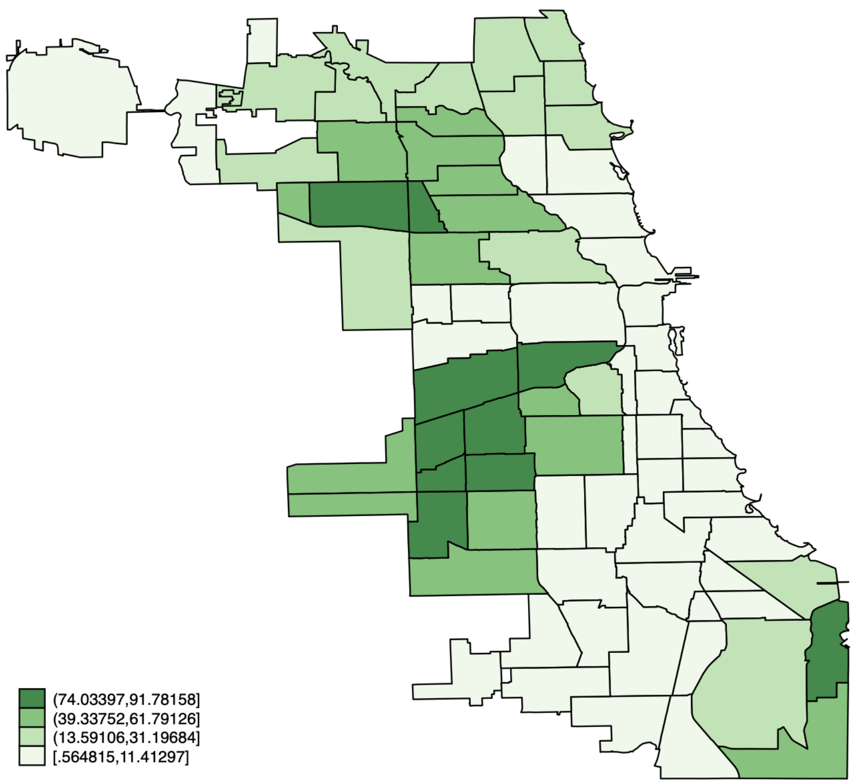
Notes: The map illustrates how CAs of Chicago are assigned to four different clusters in terms of percentage of White population via k-means clustering. The CA colored in the darkest shade of green is the only one composing the Asian area. The legend on the left of the figure reports the thresholds for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

Figure B.6: Distribution of Black population in Chicago



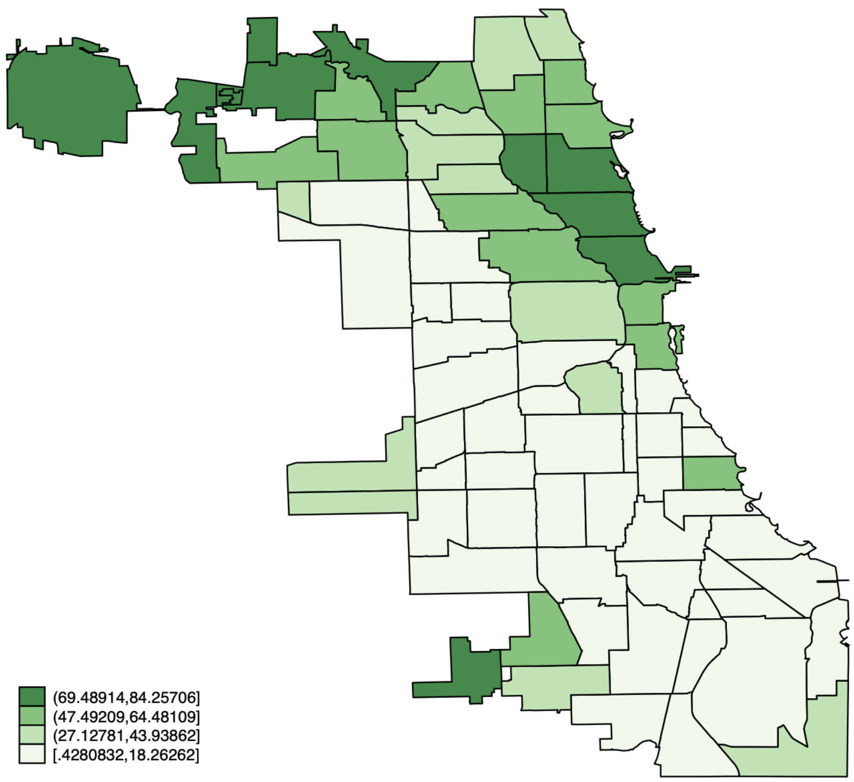
Notes: The map illustrates how CAs of Chicago are assigned to four different clusters in terms of percentage of Black population via k-means clustering. Areas colored in the darkest shade of green are those belonging to the Black area. The legend on the left of the figure reports the thresholds for the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

Figure B.7: 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.8: 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.