If You Can't Beat Them Join Them: Empirical Assessment into How Integrating Conventional Taxis on the Uber App Impacts Conventional Taxi Ridership

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Abstract

Since the emergence of car-hailing platforms like Uber, conventional taxi ridership has taken a severe hit. Taxi-hailing apps like Curb and Arro have allowed conventional taxis to jump on the platform economy bandwagon and offer services similar to car-hailing platforms. Despite the emergence of these taxi-hailing apps, high switching costs of popular car-hailing platforms (Uber, Lyft, etc) restrict the ridership volumes of conventional taxis. Recently, the car-hailing platform, Uber has started to add conventional taxis on its app under increasing pressure from Cities and conventional taxi associations. Such integrations have the potential to increase conventional taxi ridership by providing Uber users with information about an additional travel option. In this paper, I investigate the impacts of conventional taxi integration on the Uber app in New York City and Chicago using a Differences-in-Differences approach. Results show that the integration of conventional taxis to the Uber app led to a statistically significant increase in conventional taxi ridership in both cities. The paper provides insights into how Cities can regulate car-hailing platforms and tackle their high switching costs which make them anti-competitive, and hence enable conventional taxis to compete with these car-hailing platforms more efficiently.

JEL classification: L91, L86

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1 Introduction

1.1 Motivation

Ever since the emergence of ride-hailing platforms like Uber and Lyft, conventional taxi ridership has plummeted. This is illustrated by Figure 1 which compares the average daily ridership of ride-hailing platforms and conventional yellow taxis in New York City (NYC hereafter) for each month from January 2015 to April 2024. While ride-hailing saw a meteoric rise in average daily ridership during the period, conventional yellow taxis in the city saw a four-fold reduction in the average daily yellow taxi trips from 411,238 in January 2015 to 115,813 in April 2024. As Figure 2 depicts, the market share of ride-hailing rose from 12 percent to 86 percent during this roughly 9-year span.

The "Uberization" of the taxi space has impacted driver earnings and mental health. Berger et al. (2018) show that conventional taxi drivers experienced a relative earnings decline of about 10 percent subsequent to Uber's entry into a new market in the United States (US hereafter). Apouey and Stabile (2022) show that Uber's entry in the London market led to worsening mental health outcomes for conventional taxi drivers.

The emergence of electronic hailing apps for conventional taxis like Curb and Arro (called 'taxi-hailing' apps hereafter with 'car-hailing' used for non-taxi e-hailing platforms like Uber and Lyft) has allowed conventional taxis to jump on the e-hailing bandwagon. Such taxi-hailing apps allow riders to request conventional taxis via an app, make payments via the app and see upfront trip prices at the time of booking a ride.

Despite the emergence of these taxi-hailing mobile apps, high switching costs of well-established car-hailing apps like Uber and Lyft can limit the ridership potential of conventional taxis and make these popular car-hailing platforms anti-competitive (Wolff (2019)). For riders, it is less costly to use one service provider instead of multi-homing which refers to switching between multiple apps before deciding on which platform's service to use. There could be multiple reasons prompting users to avoid multi-homing: familiarizing oneself with the user interface and working of a new app; signing up to a new platform by entering user details; entering payment information to a new platform; gaining a reputation of being a good consumer by having a good customer rating; etc. Take the example of an Uber user planning on undertaking a specific journey. Despite the availability of taxi-hailing apps, car-hailing apps other than the Uber app and apps for services like bike-sharing, there is a possibility that this user might not seek pricing, travel time and other information from these other apps due to the high switching cost of the Uber app. Even if these other apps serve as a more viable travel option due to lower pricing and travel time, the switching costs faced by the Uber user could restrict mutli-homing.

These switching costs of popular car-hailing platforms could lead to an information deficit for users whereby they are deprived of potentially more feasible travel options. Hence, the addition of an outside travel option to popular car-hailing apps could potentially lead to an increase in the usage of these outside options as such integrations could reduce the information deficit users of popular car-hailing apps face.

1.2 Research Objectives, Context and Overview of Findings

To investigate the hypothesis of whether the addition of an outside travel option to popular car-hailing apps leads to increased ridership of the outside travel option, in this paper, I study whether the addition of conventional taxis to the Uber app in NYC and Chicago led to an increase in conventional taxi ridership in these two cities using a Differences-in-Differences regression approach.

In NYC, there are multiple conventional taxi services like green taxis (taxis that can pick up passengers at all locations in NYC except for south of East 96th Street and West 110th Street in Manhattan) and yellow taxis (taxis allowed to pick up passengers everywhere in NYC). In September of 2022, only one of NYC's conventional taxi services, i.e. yellow taxis, was listed on the Uber app as a travel option after which Uber app users could see how long it would take the nearest yellow taxi to reach them, see the trip fare for their desired journey and book a yellow taxi via the Uber app. The trip fare for conventional yellow taxis booked via the Uber app was the same as the fare for UberX (Uber's standard flagship option).

Additionally, in August of 2023, Uber took the integration up a notch. If a yellow taxi was closer than an UberX (Uber's standard offering), Uber app users who requested an UberX trip were automatically matched with a yellow taxi. After automatically matching Uber users who had requested an UberX ride with a yellow taxi if a yellow taxi was closer, users were notified that they had been matched with a yellow taxi; they could reject the yellow taxi offering as they were given the option to be re-matched with an UberX driver or to cancel their ride.

Using Differences-in Differences (Diff-in-Diff) regression models, I investigate the impacts of these two interventions in NYC on yellow taxi ridership. To determine the impacts of the two interventions on yellow taxi ridership in the city, I make use of three Diff-in-

Diff regression specifications. In one of these specifications, I compare e-hailed yellow taxi ridership (treatment group) with street hailed yellow taxi ridership (control group). In another specification, I compare e-hailed yellow taxi ridership, which is the treated group, with the ridership of the car-share platform, Lyft (control group). Lastly, I use a Differences-in-Differences specification to compare e-hailed yellow taxi ridership (treated group) with e-hailed green taxi ridership (control group) while restricting the analysis to the areas of NYC where green taxis are allowed to operate; since green taxis were not listed on the Uber app, this specification implies the treatment effect of integrating yellow taxis on the Uber app.

The results indicate that both the interventions (i.e. the intervention in 2022 and 2023) led to a statistically significant increase in yellow taxi ridership in the city; this is confirmed by the results of all three regression specifications.

For Chicago, I similarly use a Differences-in-Differences regression model to estimate the impact of integrating conventional taxis on the Uber app. Conventional taxis were integrated on the Uber app in April 2024 after which Uber app users could see how long it would take the nearest yellow taxi to reach their pickup location, see the trip fare and book a ride. In the regression model, I use conventional taxis as the treatment group and car-share platforms as the control group. The regression results indicate that the integration of conventional taxis on Uber in Chicago led to a statistically significant increase in conventional taxi ridership in the city.

This paper contributes to the literature on multimodal transport (Heinen and Mattioli (2019)), behavioral changes in response to changing defaults on digital platforms (Decarolis et al. (2024)) and the impacts of changing travel options on transport platforms (Thorne et al. (2024)).

1.3 Takeaways for Policymakers, Platforms and Conventional Non-platform Services

This research has important repercussions for policymakers. Policymakers around the world are heavily engaged in the regulation of two-sided platform services (Airbnb, car-hailing, etc) for reasons including their impacts on conventional non-platform services (like hotels in the case of Airbnb; and conventional taxis and public transport in the case of car-sharing services). As policymakers around the world try to regulate two-sided platforms with high switching costs, they can benefit from this research as it zooms in on how conventional services can better compete with their two-sided platform counterparts via the integration of conventional services on the apps of their two-sided platform counterparts.

Making such integrations an imperative pre-condition upon certain popular two-sided platforms for operating in Cities could allow Cities to clamp down on 'Walled Gardens'. The phrase Walled Gardens is often used for two-sided platforms like car-sharing platforms (Zipper (2019), Wolff (2019)) to emphasize a tactic used by various two-sided platforms whereby platforms only list their own services on their apps and simultaneously disallow their services from being listed on other apps. The rationale for platforms behind these Walled Gardens is to lock users in on their apps and achieve large usage volumes for their own services by not allowing users to see outside travel options on their apps and also not allowing people to see their own services on other apps (as this could result in greater competition between them and other transport services by dismantling the multi-homing problem).

Platforms often take measures to ensure that these Walled Gardens remain intact. For instance, in 2019, the car-hailing app, Lyft, which also owns the bike-sharing service, Citibike in NYC and lists Citibike as a travel option on the Lyft app, blocked the transport aggregator app, Transit, from allowing the purchase of bike-sharing passes in NYC via the Transit app, a move that prompted Transit to accuse Lyft of using Walled Garden tactics Transit (2019). Keeping in mind the high switching costs users of two-sided platforms face and the Walled Garden tactics often employed by car-sharing platforms and digital platforms at large, this research will inform policymakers on the gains conventional services can get from being integrated with two-sided platforms offering similar services.

Along with policymakers, the research also has important implications for two-sided platforms and businesses providing conventional services. The results of this paper confirm the increased procurement of a conventional service integrated on a two-sided platform post-integration, which has important revenue implications for two-sided platforms as they can charge a commission for conventional services procured via their apps (just like Uber does for conventional taxi trips procured via its platform). Also, conventional service providing businesses can benefit from this research as it shows that they can benefit from increased conventional service usage volumes and hence revenue.

The next sections of this paper will delve into the data used for the analysis, methods utilized, results obtained and conclusions of the research.

2 Data

For the case of NYC, I make use of open-source data for conventional taxi and car-share trips made available by the City of New York. The City of New York has made conventional taxi trip data publicly available for taxi trips done in the city since 2009. The data for yellow taxis is available from 2009 onwards and for green taxis, data is available for trips since August of 2013, which is when green taxis were introduced in the city. Additionally, the City provides car-share trip data for trips done since 2015.

The taxi data contains information regarding the specifics of all taxi pickups done in the city since 2009 for yellow taxis and 2013 for green taxis. Among other things, the data contains information regarding the pickup date; drop off date; pickup time; drop off time; ride fare (including all surcharges); tips given; number of passengers in the car; distance of the trip; neighborhood where the passenger was picked up; neighborhood where the passenger was dropped off; method used for payment; and ride source (e-hail or street hail). The car-share data, among other characteristics, encompasses information regarding the car-share service provider company; pickup date; drop off date; pickup time; drop off time; ride fare (including all surcharges); tips given; distance of the trip; neighborhood where the passenger was picked up; and neighborhood where the passenger was dropped off.

For the case of Chicago, I make use of publicly available taxi trip data made available by the City for trips done since 2013, in addition to car-share data the City has made public for trips done since 2018.

In addition to other variables, the data encompasses information on the pickup location; drop off location; pickup time; drop off time; fare (including surcharges); tolls; pickup neighborhood; drop off neighborhood; method used for payment; and the taxi company with which the specific taxi is affiliated.

Among other specifications, the car-share data for Chicago contains information regarding the pickup date; drop off date; pickup time; drop off time; ride fare (including all surcharges); tipping; trip distance; pickup neighborhood; and neighborhood where the passenger was dropped off.

3 Methods

In New York City, the listing of conventional taxis on the Uber app in September of 2022 provides a natural experimental setup for which I make use of differences-in-differences regression models to investigate the impact this integration had on conventional taxi ridership in the city.

As alluded to earlier, the integration of taxis on the Uber app in NYC in 2022 only entailed the integration of yellow taxis while green taxis were not added to the app. After the integration, Uber app users could see how long it would take the nearest yellow taxi to arrive at their desired pickup point; see fare prices for yellow taxis; and book a yellow taxi ride. Riders requesting yellow taxis via the Uber app were matched with yellow taxi drivers on the Curb and Arro apps, which are conventional taxi e-hail apps in the US.

Since the data for NYC allows differentiating between e-hailed yellow taxi rides (i.e. yellow taxi rides hailed using mobile apps) and street-hailed yellow taxi rides, I make use of a differences-in-differences model to compare the before and after ridership of e-hailed yellow taxis and street-hailed yellow taxis. In this regression model, e-hailed yellow taxis serve as the treatment group and street-hailed yellow taxis serve as the control group. The differences-in-differences regression equation is as follows:

$$ln(Count_{dtfb}) = \beta_1 Ehail + \beta_2 Ehail \times Post_t + X_{dtb} + \delta_d + \gamma_t + \sigma_b + \epsilon_{dtfl} \quad (1)$$

The outcome variable $Count_{dtfb}$ of the differences-in-differences equation represented by equation 1 is the taxi ridership count on date d, at time t, for fare level f and in borough b. The variable X_{dtb} is a control for the trip fare. *Ehail* is a dummy variable which is one for e-hailed yellow taxi trips and zero for street-hailed yellow taxi trips. The variable *Post* is a dummy variable which is zero for pre-Uber integration time periods and one post-integration. δ_d represents fixed effects for the date, γ_t represents time fixed effects and σ_n represents fixed effects for the NYC borough where the pickup took place. β_2 i.e. coefficient of the interaction term is the coefficient of interest and it will indicate the treatment effect.

Another Differences-in-Differences regression model compares e-hailed yellow taxi ridership with the ridership of the popular car-share platform, Lyft; the former serves as the treatment group and the latter is the control group. The equation for this Diff-in-Diff model is as follows:

$$ln(Count_{dtfb}) = \beta_1 Yellow + \beta_2 Yellow \times Post_t + X_{dtb} + \delta_d + \gamma_t + \sigma_b + \epsilon_{dtfl} \quad (2)$$

In equation 2, the variable *Yellow* is a dummy variable which is one for e-hailed yellow taxi rides and zero for Lyft rides. For a robustness check, I also undertake a Diff-in-Diff regression comparing street-hailed yellow taxi ridership with Lyft ridership using the same equation i.e. equation 2. The regression results for the case where *Yellow* represents e-hailed yellow taxi pickups should show statistically significant results while the case where *Yellow* represents street-hailed pickups should give statistically insignificant results.

Additionally, for NYC, I undertake a Differences-in-Differences analysis comparing e-hailed yellow taxi trip count with e-hailed green taxi trip count in the NYC boroughs where green taxis operate. The Diff-in-Diff regression equation is as follows:

$$ln(Count_{dtfb}) = \beta_1 Yellow + \beta_2 Yellow \times Post_t + X_{dtb} + \delta_d + \gamma_t + \sigma_b + \epsilon_{dtfl} \qquad (3)$$

The variable *Yellow* in this equation is a dummy variable which is one for e-hailed yellow taxi trips and zero for e-hailed green taxi rides.

In 2023, the Uber and yellow taxi integration in NYC went up a notch; if a yellow taxi was closer than an UberX (Uber's standard offering), Uber app users who requested an UberX trip were automatically matched with a yellow taxi. After the automatic matching with a yellow taxi cab, Uber users were notified that they had been matched with a yellow taxi; they could reject the yellow taxi offering as they were given the option to be re-matched with an UberX driver or to cancel their ride. I make use of equations 1, 2 and **??** to check the impacts of this intervention.

Just as for NYC, for the case of Chicago, a Differences-in-Differences regression model is utilized to understand the ridership implications for conventional taxis in response to the listing of taxis on the Uber app in April 2024. Just like the integration in NYC in September of 2022, this integration in Chicago led to conventional taxis appearing as a travel option on the Uber app, Uber users being able to check how long it would take the nearest taxi to reach their pickup point and Uber users being able to book a conventional taxi via the Uber app.

For the case of Chicago, a Diff-in-Diff model comparing conventional taxi ridership and car-share ridership is used. The regression equation is as follows:

$$ln(Count_{dtfn}) = \beta_1 Taxi + \beta_2 Taxi \times Post_t + X_{dtn} + \delta_d + \gamma_t + \sigma_n + \epsilon_{dtfl} \qquad (4)$$

n represents the pickup neighborhood in Chicago where the taxi or car-share pickup took place. $Taxi$ is a dummy variable which is one for conventional taxi trips and zero for car-share trips. Unlike the data for NYC, the data for Chicago does not allow differentiating between street hailed and e-hailed taxi trips. The data does include the payment method used for the trip; to make sure only e-hailed conventional taxi trips are used in the Diff-in-Diff analysis, I use conventional taxi trips where the payment is made directly in-app to the e-hail service and remove trips where the payment method is credit card or cash (since trips with these two payment methods contain both e-hailed and street-hailed trips).

4 Results

Figure 3 illustrates the weekly ridership counts for e-hailed and street hailed yellow taxis in NYC in 2022. For visual purposes, the trend for e-hailed yellow taxis has been scaled up as the ridership volume of e-hailed yellow taxis is lower than that of street hailed yellow taxis. As the graph indicates, the integration of yellow taxis on Uber in 2022 (illustrated by the dashed vertical line) led to a divergence in the weekly counts of the two services. This is confirmed by Table 1, which is the regression table for Equation 1 and compares the ridership of e-hailed and street hailed yellow taxis. There is a statistically significant increase in e-hailed yellow taxi ridership when compared with street hailed yellow taxi ridership, as illustrated by the coefficient of the interaction term in the table (controlling for the fare and adding all the fixed effects). The table hence confirms the treatment effect of listing yellow taxis on the Uber app as there was a statistically significant increase in e-hailed yellow taxi ridership relative to street hailed ridership.

Similarly, Figure 6 compares e-hailed and street hailed yellow taxi ridership in 2023. The graph shows a clear divergence of the two services when Uber started automatically matching UberX requests with yellow taxis (as indicated by the trend after the dashed vertical line, which is when the intervention took place). The causal impact of the intervention is illustrated by Table 5, which shows that there was a statistically significant increase in e-hailed yellow taxi ridership relative to street hailed yellow taxi ridership after the intervention.

Figure 4 shows the weekly trip counts of e-hailed yellow taxis and Lyft car-share in 2022. For visual purposes, E-hailed yellow taxi ridership, which is lower than the ridership for Lyft, has been scaled up. In the figure, the vertical dashed line represents the week yellow taxis were listed on Uber in 2022. The graph shows an increase in e-hailed yellow taxi ridership relative to Lyft after the intervention. This is confirmed by Table 2, which is the regression table for Equation 2 and compares e-hailed yellow taxi ridership and Lyft car-share ridership. The coefficient of the interaction term is statistically significant (as depicted by the last column of the table that encompasses all the fixed effects and controls for the fare), confirming the treatment effect of the listing of yellow taxis on Uber in 2022. For a robustness check, I compare street hailed yellow taxi ridership with Lyft car-share ridership; Table 3 is the regression table modeling this relationship. The coefficient of the interaction term for this regression should be insignificant as is confirmed by the table, since the listing of yellow taxis on Uber should only have impacted e-hailed yellow taxi ridership without impacting street hailed yellow taxi ridership.

Figure 7 depicts the increase in e-hailed yellow taxi ridership relative to Lyft car-share ridership in 2023 when Uber started automatically matching UberX requests with yellow taxis. Table 6 shows that the 2023 intervention led to a statistically significant increase in e-hailed yellow taxi ridership relative to Lyft car-share ridership (after controlling for the fare and adding all the fixed effects). Table 7 depicts a robustness check comparing street hailed yellow taxi ridership with Lyft car-share ridership. The coefficient of the interaction term is not statistically significant since the intervention should only impact e-hailed yellow taxi trips without changing street hailed yellow taxi trip volume.

Lastly, for NYC, I compare e-hailed yellow taxi ridership with e-hailed green taxi ridership. This analysis is restricted to the locations in NYC where green taxis are allowed to operate. Temporal weekly ridership plots (Figure 5 for the 2022 intervention and Figure 8 for the 2023 intervention) indicate increasing ridership of e-hailed yellow taxis relative to e-hailed green taxis post-intervention. In both these plots, e-hailed green taxi ridership, which is lower than the ridership of e-hailed yellow taxis, has been slightly scaled up for visual purposes. Regression tables (Table 4 for the 2022 intervention and Table 8 for the 2023 intervention) corresponding to Equation 3 imply a statistically significant increase in e-hailed yellow taxi ridership relative to e-hailed green taxi ridership post-intervention in 2022 and 2023.

Hence, all the three regression models (Equations 1, 2 and 3) utilized for investigating the treatment effects of the 2022 and 2023 interventions in NYC indicate a statistically significant increase in yellow taxi ridership post intervention.

To check the ridership implications for conventional taxis after the listing of conventional taxis on Uber in Chicago 2024, I make use of the weekly ridership trend illustrated by Figure 9. The figure compares conventional taxi ridership with car-share platform trip counts. It can be seen that the intervention (depicted by the dashed vertical line) led to an increase in conventional taxi ridership since there is an increase in conventional taxi ridership relative to car-share ridership. In the temporal plot, conventional taxi ridership (which is less than the ridership for car-share) has been slightly scaled up for visual purposes. Table 9, which is the regression table for equation 4, indicates the treatment effect of the intervention; there is a statistically significant increase in conventional taxi ridership relative to car-share ridership (after controlling for the fare and adding the fixed effects). Hence, just as the 2022 intervention in NYC, a similar intervention in Chicago (whereby conventional taxis were listed on the Uber app) led to a statistically significant increase in conventional taxi ridership in the city.

5 Conclusions

Since the emergence of popular digital platform-based services like Uber and Airbnb, their traditional counterparts (conventional taxis, hotels, etc) have taken a serious hit. The high switching costs of such platforms make them anti-competitive.

Recently, especially in the transport sector, digital platforms have been adding conventional services to their apps. Zooming in on the integration of traditional taxis to the Uber app in the US cities of NYC and Chicago, this paper shows that such interventions can have positive impacts on traditional transport services, allowing them to compete with their digital counterparts.

Using a Differences-in-Differences approach, I show that the listing of traditional taxis to the Uber app in NYC in 2022 and Chicago in 2024 led to a statistically significant increase in traditional taxi ridership in both these cities. These results indicate that the high switching costs of popular car-sharing platforms restrict users from multi-homing, leaving them with an information deficit about viable options they can make use of for their desired journey. This makes car-share platforms anti-competitive and restricts the ridership potential of alternative travel options like conventional taxis. Considering this, listing conventional taxis on a popular car-sharing service like Uber can reduce the switching costs users of these platforms face and hence reduce the information deficit these platforms entail.

The research also shows that when Uber automatically started matching requests for UberX with conventional taxis, there was a statistically significant increase in conventional taxi ridership.

Policymakers can make use of the findings from this paper to make it imperative for popular car-sharing platforms to list conventional taxis on their apps, and hence improve competition between the two. The results indicate that these interventions can also benefit conventional taxi drivers and businesses that operate conventional taxis due to increased trip volumes. Lastly, car-share platforms can infer from these findings that such integrations benefit them as well since they can charge commissions on conventional taxi trips undertaken via their platforms and increase their revenues.

6 Figures

Figure 1: Illustration of the Nosedive in Conventional Taxi Ridership as Ride-hail Apps Usage Increased in NYC

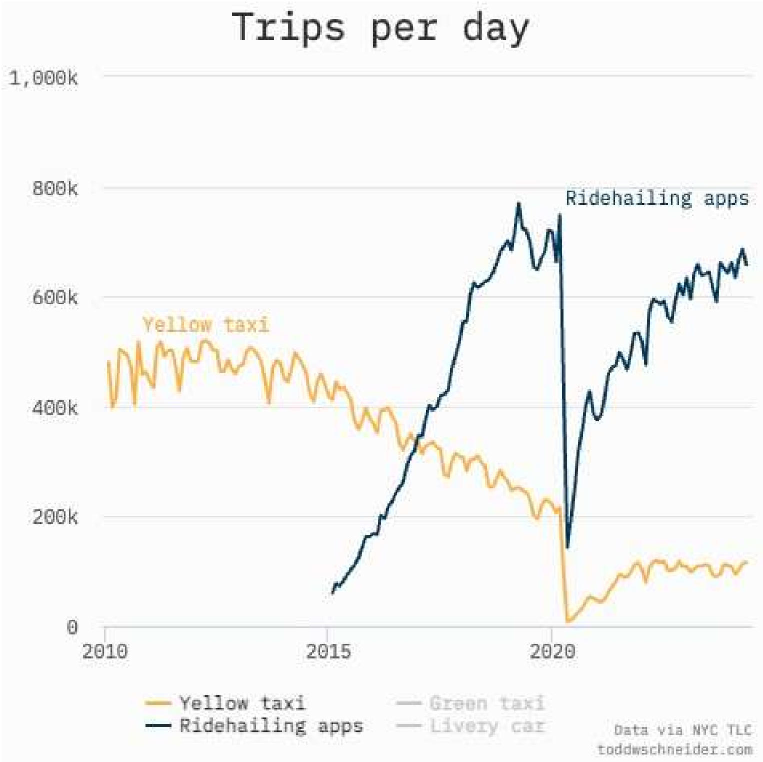


Figure 2: Visualisation of the Temporal Market Share of Ride-hailing Apps in NYC

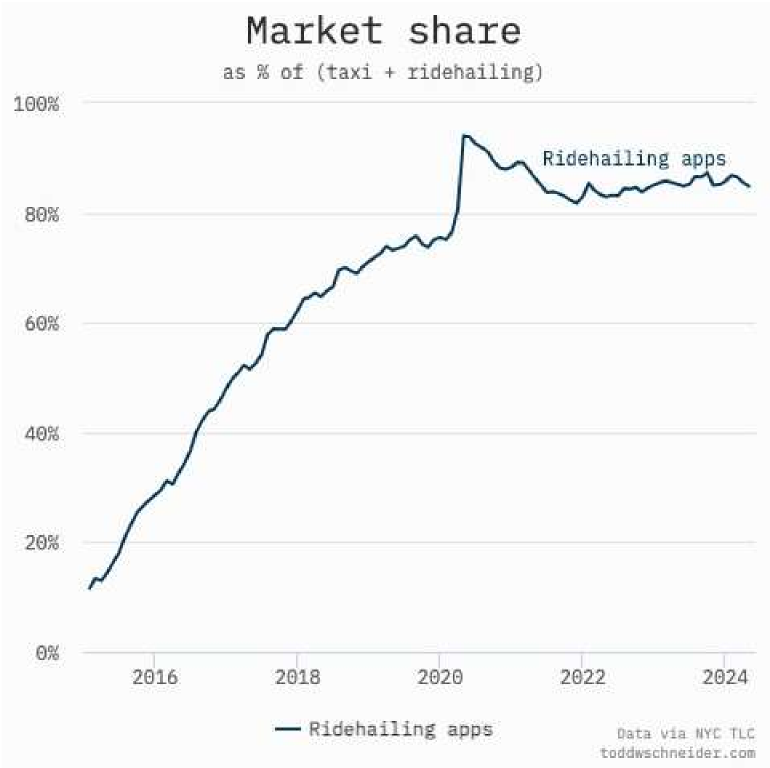


Figure 3: Daily Trip Count for E-hailed and Street Hailed Yellow Taxis in NYC (2022). The Trend for E-hailed Yellow Taxis Has Been Scaled Up for Visual Purposes and Public Holidays Have Been Excluded from the Weekly Counts

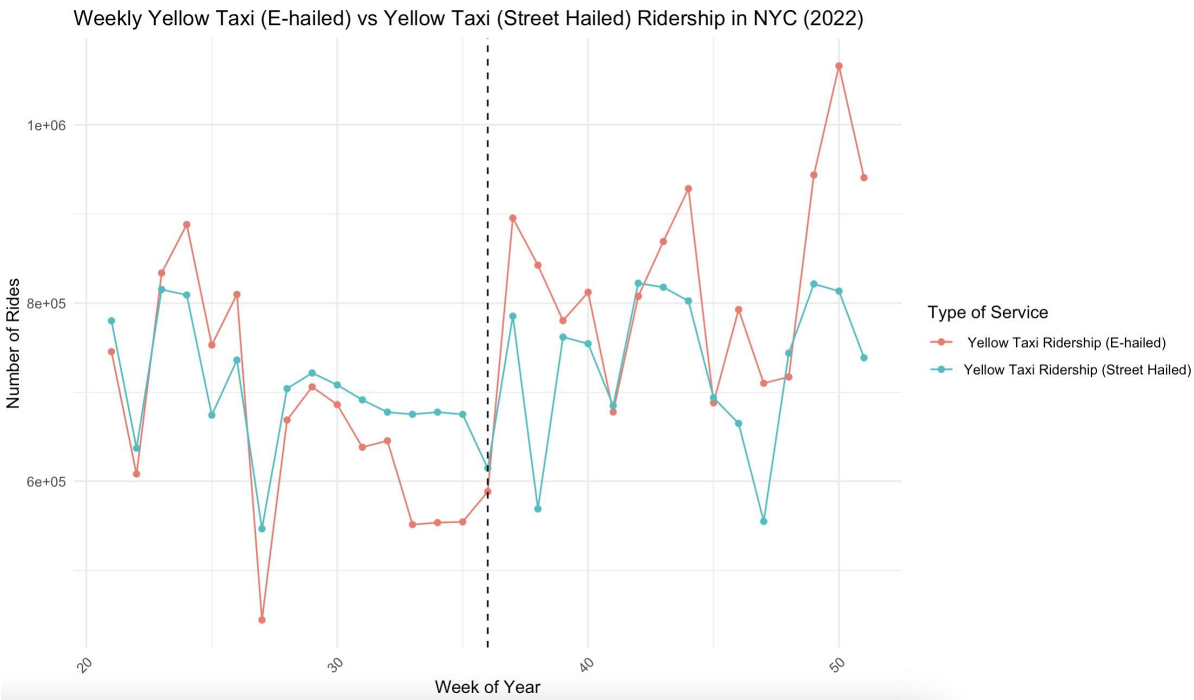


Figure 4: Weekly Trip Count for Yellow Taxis (E-hailed) and Lyft Car-share in NYC (2022). The Trend for E-hailed Yellow Taxis Has Been Scaled Up for Visual Purposes and Public Holidays Have Been Excluded from the Weekly Counts

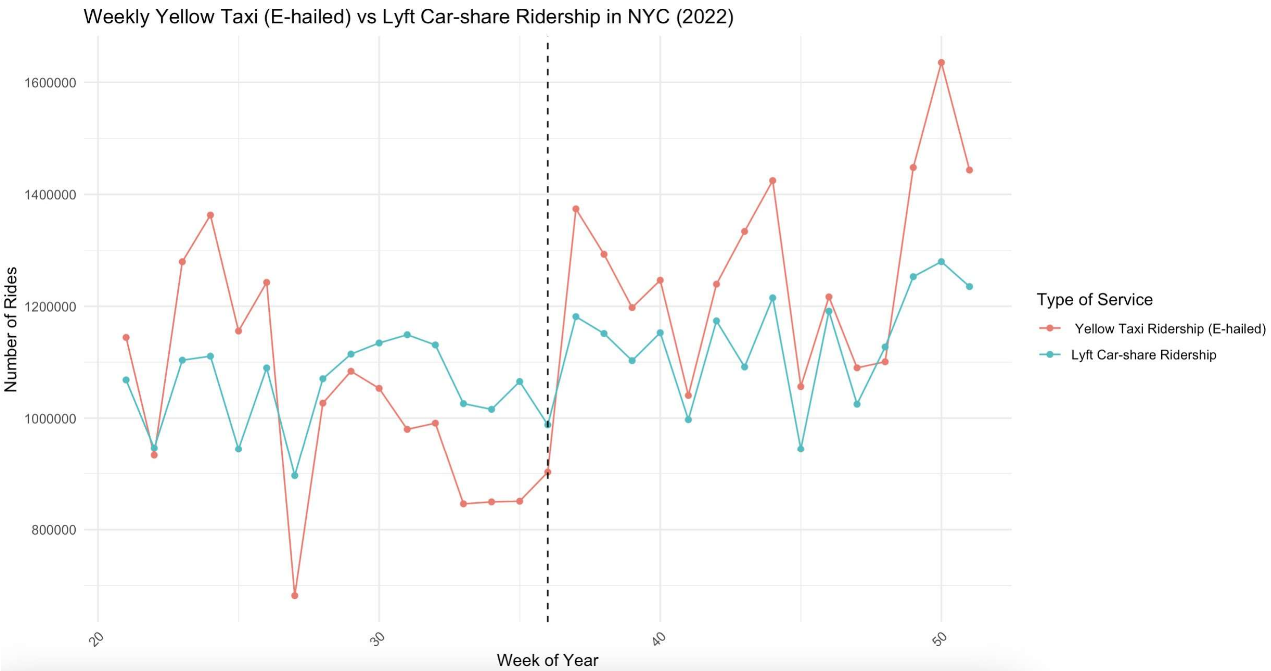


Figure 5: Weekly Trip Count for Yellow Taxis (E-hailed) and Green Taxis (E-hailed) in NYC (2022). The Trend for E-hailed Green Taxis Has Been Scaled Up for Visual Purposes and Public Holidays Have Been Excluded from the Weekly Counts

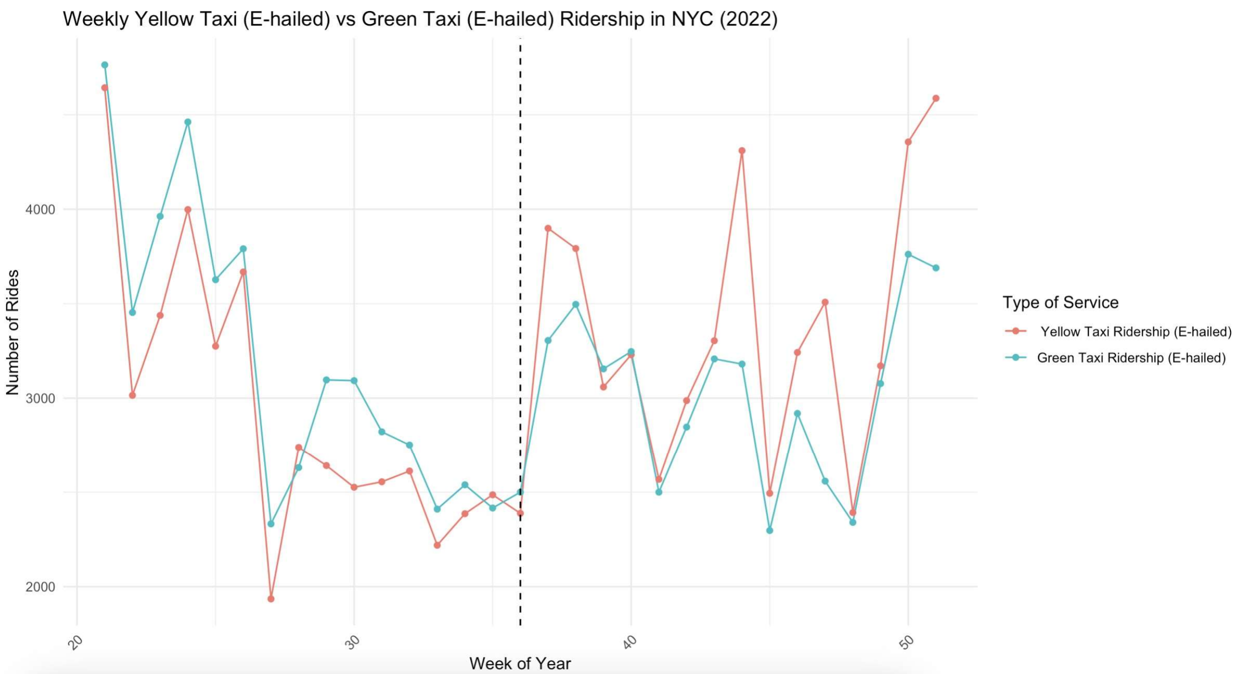


Figure 6: Weekly Trip Count of E-hailed and Street Hailed Yellow Taxis in NYC (2023). The Trend for E-hailed Yellow Taxis Has Been Scaled Up for Visual Purposes and Public Holidays Have Been Excluded from the Weekly Counts

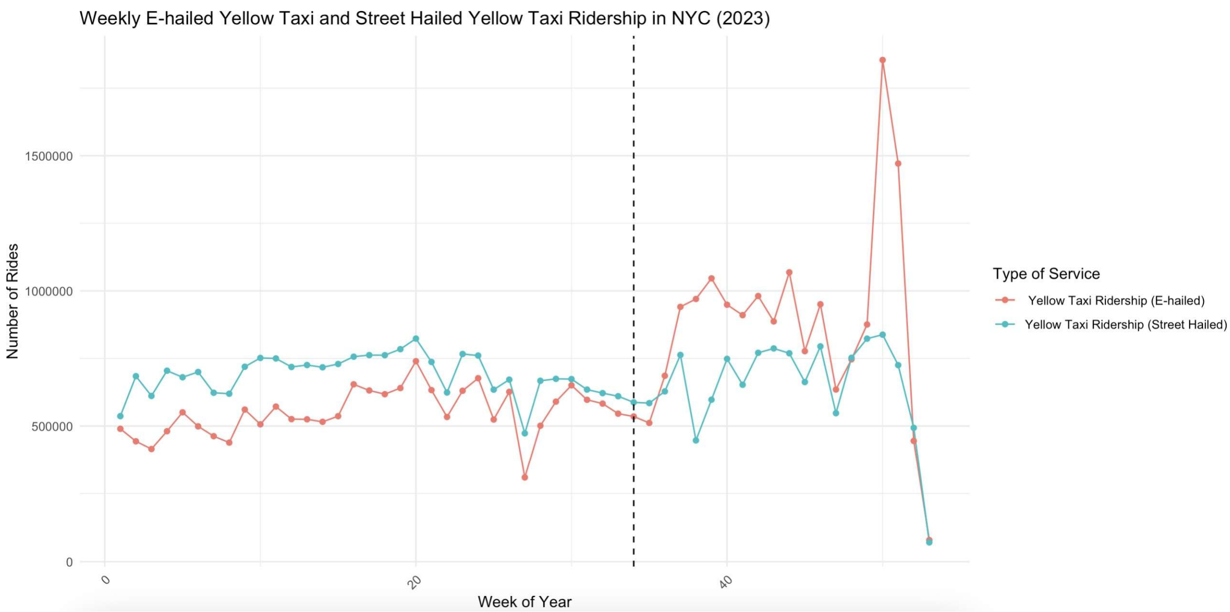


Figure 7: Weekly Trip Count for Yellow Taxis (E-hailed) and Lyft Car-share in NYC (2023). The Trend for E-hailed Yellow Taxis Has Been Scaled Up for Visual Purposes and Public Holidays Have Been Excluded from the Weekly Counts

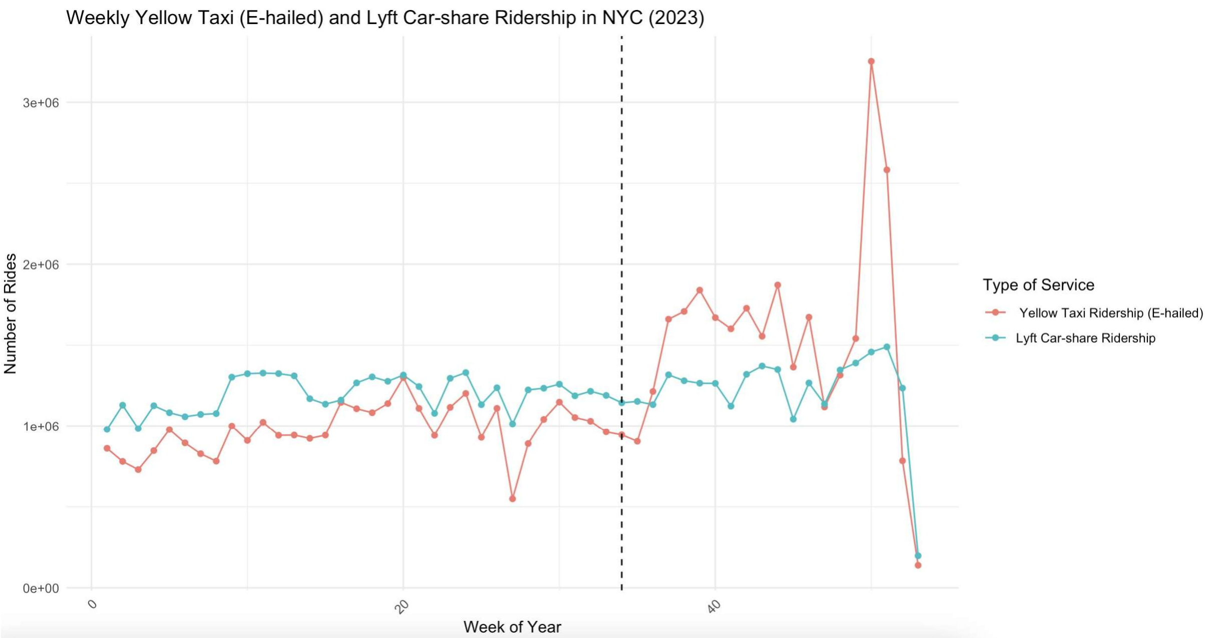


Figure 8: Weekly Trip Count of E-hailed Yellow and Green Taxis in NYC (2023). The Trend for E-hailed Green Taxis Has Been Scaled Up for Visual Purposes and Public Holidays Have Been Excluded from the Weekly Counts

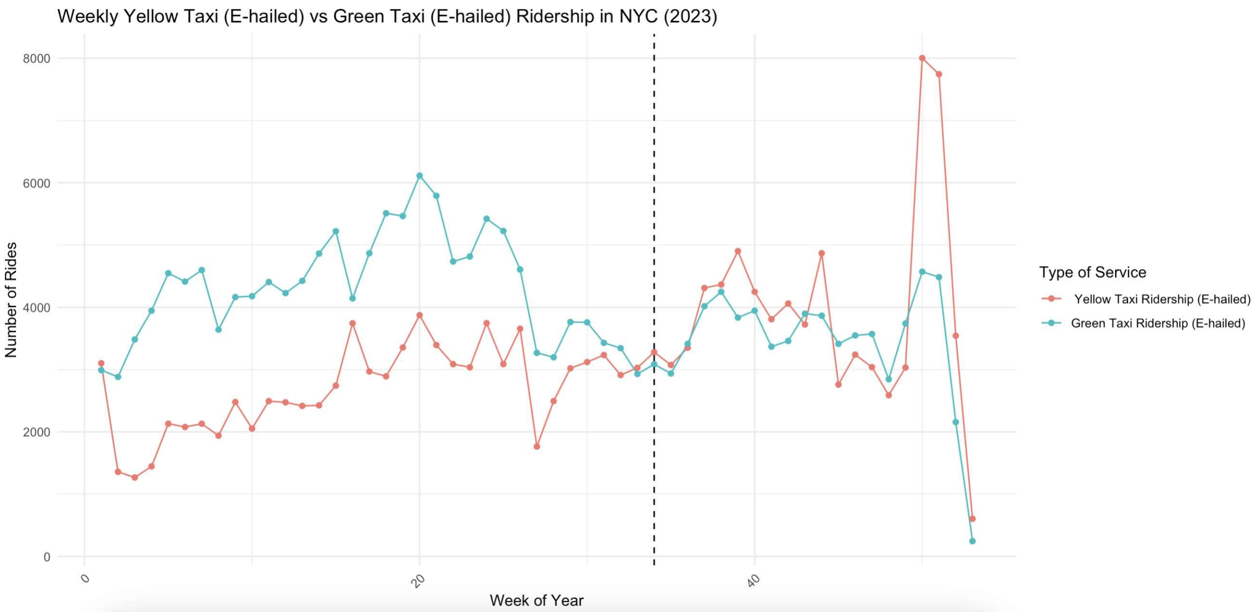
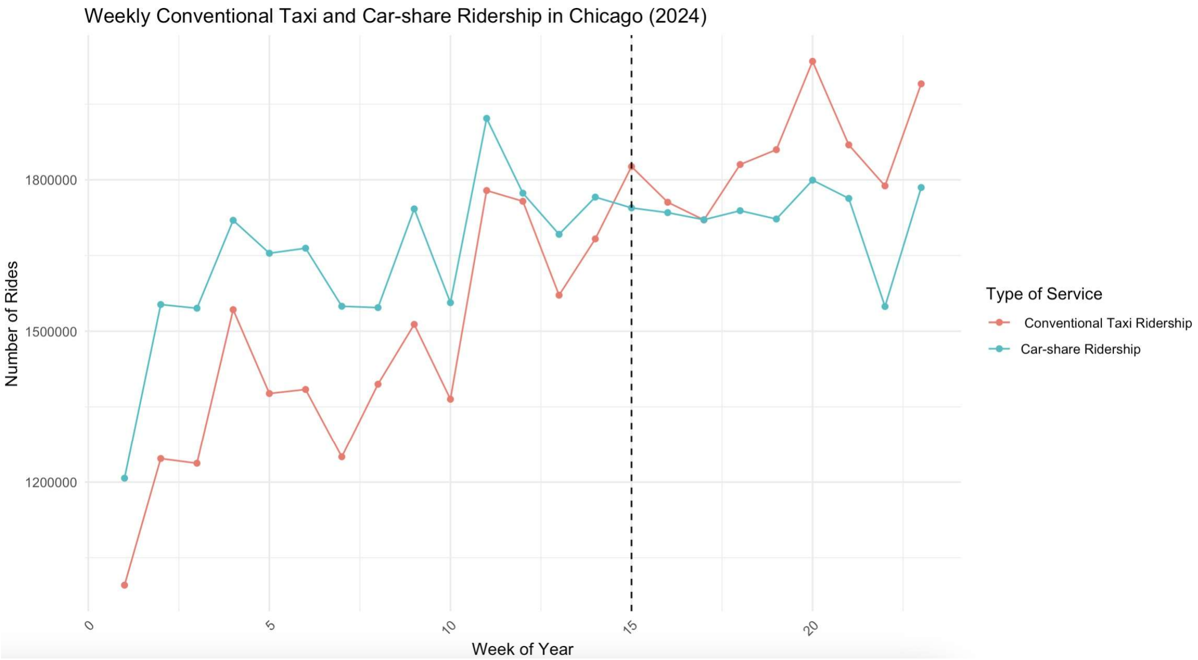


Figure 9: Weekly Conventional Taxi Ridership (E-hailed) and For-hire Car-share Ridership in Chicago (2024)



7 Tables

Table 1: Diff-in-Diff Comparing E-hailed and Street Hailed Yellow Taxi Ridership. This Table is for NYC - Pre-post Analysis for Yellow Taxi Integration On Uber in 2022

Dependent Variable:	ln(Count)			
Model:	(1)	(2)	(3)	(4)
Variables				
Ehail	-3.428***	-3.445***	-2.933***	-2.168***
	(0.0179)	(0.0220)	(0.1003)	(0.0712)
Ehail × Post	0.2363*	0.1899*	0.1059***	0.0772***
	(0.1054)	(0.0762)	(0.0191)	(0.0172)
Control				
Fare	No	Yes	Yes	Yes
Fixed-effects				
Pickup Date	Yes	Yes	Yes	Yes
Pickup Time			Yes	Yes
Pickup Borough				Yes
Fit statistics				
Observations	368	3,247	70,307	161,232
R^2	0.95874	0.93492	0.87036	0.70280
Within R^2	0.95686	0.93370	0.85656	0.54482

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 2: Diff-in-Diff Comparing E-hailed Yellow Taxi Ridership and Lyft Car-hail Ridership. This Table is for NYC - Pre-post Analysis for Yellow Taxi Integration On Uber in 2022

Dependent Variable:	ln(Count)			
Model:	(1)	(2)	(3)	(4)
Variables				
Yellow	-3.857***	-3.134***	-3.580***	-3.749***
	(0.0215)	(0.0227)	(0.0365)	(0.0331)
Yellow × Post	0.1425***	0.0991**	0.1401***	0.0717***
	(0.0263)	(0.0351)	(0.0123)	(0.0132)
Control				
Fare	No	Yes	Yes	Yes
Fixed-effects				
Pickup Date	Yes	Yes	Yes	Yes
Pickup Time			Yes	Yes
Pickup Borough				Yes
Fit statistics				
Observations	368	3,160	64,118	202,735
R^2	0.99781	0.83303	0.80709	0.78564
Within R^2	0.99780	0.83142	0.80414	0.76034

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 3: Diff-in-Diff Comparing Street Hailed Yellow Taxi Ridership and Lyft Car-hail Ridership. This Table is for NYC - Pre-post Analysis for Yellow Taxi Integration On Uber in 2022

Dependent Variable:	ln(Count)			
Model:	(1)	(2)	(3)	(4)
Variables				
Yellow	-0.4283***	0.3000***	-0.6947***	-2.202***
	(0.0165)	(0.0364)	(0.1415)	(0.0319)
Yellow × Post	-0.0938	-0.0673	0.0413*	0.0098
	(0.1038)	(0.0882)	(0.0152)	(0.0140)
Control				
Fare	No	Yes	Yes	Yes
Fixed-effects				
Pickup Date	Yes	Yes	Yes	Yes
Pickup Time			Yes	Yes
Pickup Borough				Yes
Fit statistics				
Observations	368	3,217	72,557	264,587
R^2	0.59363	0.74064	0.76233	0.67222
Within R^2	0.32167	0.73620	0.73313	0.59266

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 4: Diff-in-Diff Comparing E-hailed Yellow Taxi and E-Hailed Green Taxi Ridership. This Table is for NYC (Except for Places Where Green Taxis Don't Operate i.e. Below East 96th Street and West 110th Street in Manhattan) - Pre-post Analysis for Yellow Taxi Integration On Uber in 2022

Dependent Variable:	ln(Count)			
Model:	(1)	(2)	(3)	(4)
Variables				
Yellow	0.5591***	0.2780***	0.2938***	0.2100***
	(0.0234)	(0.0313)	(0.0445)	(0.0245)
Yellow × Post	0.1824***	0.1530***	0.1208***	0.0756***
	(0.0326)	(0.0442)	(0.0177)	(0.0159)
Fixed-effects				
Fare	No	Yes	Yes	Yes
Fixed-effects				
Pickup Date	Yes	Yes	Yes	Yes
Pickup Time			Yes	Yes
Pickup Borough				Yes
Fit statistics				
Observations	368	2,983	30,574	54,215
R^2	0.93148	0.85777	0.58192	0.32020
Within R^2	0.89907	0.85381	0.56923	0.24364

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 5: Diff-in-Diff Comparing E-hailed and Street Hailed Yellow Taxi Ridership. This Table is for NYC - Pre-post Analysis Investigating the Impacts of Automatically Matching UberX requests with Yellow Taxis in 2023

Dependent Variable:	ln(Count)			
Model:	(1)	(2)	(3)	(4)
Variables				
Ehail	-3.481***	-3.193***	-2.922***	-2.034***
	(0.0180)	(0.0220)	(0.0789)	(0.0565)
Ehail × Post	0.5787***	0.1726	0.1103***	0.0947***
	(0.1568)	(0.1119)	(0.0177)	(0.0178)
Control				
Fare	No	Yes	Yes	Yes
Fixed-effects				
Pickup Date	Yes	Yes	Yes	Yes
Pickup Time			Yes	Yes
Pickup Borough				Yes
Fit statistics				
Observations	370	3,310	71,762	171,770
R^2	0.91104	0.85228	0.79013	0.66784
Within R^2	0.90234	0.84880	0.77361	0.48398

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 6: Diff-in-Diff Comparing E-hailed Yellow Taxi Ridership and Lyft Car-hail Ridership. This Table is for NYC - Pre-post Analysis Investigating the Impacts of Automatically Matching UberX requests with Yellow Taxis in 2023

Dependent Variable:	ln(Count)			
Model:	(1)	(2)	(3)	(4)
Variables				
Yellow	-4.104***	-2.779***	-3.472***	-3.765***
	(0.0177)	(0.0239)	(0.0456)	(0.0244)
Yellow × Post	0.3644***	0.0570	0.1317***	0.1373***
	(0.0333)	(0.0356)	(0.0186)	(0.0090)
Control				
Fare	No	Yes	Yes	Yes
Fixed-effects				
Pickup Date	Yes	Yes	Yes	Yes
Pickup Time			Yes	Yes
Pickup Borough				Yes
Fit statistics				
Observations	370	3,309	67,134	215,083
R^2	0.99678	0.77392	0.74389	0.76762
Within R^2	0.99674	0.77282	0.74032	0.74555

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 7: Diff-in-Diff Comparing Street Hailed Yellow Taxi Ridership and Lyft Car-hail Ridership. This Table is for NYC - Pre-post Analysis Investigating the Impacts of Automatically Matching UberX requests with Yellow Taxis in 2023

Dependent Variable:	ln(Count)			
Model:	(1)	(2)	(3)	(4)
Variables				
Yellow	-0.6236***	0.4125***	-0.5404***	-2.193***
	(0.0164)	(0.0245)	(0.1145)	(0.0206)
Yellow × Post	-0.2143	-0.1130	-0.0023	-0.0008
	(0.1539)	(0.1163)	(0.0117)	(0.0132)
Control				
Fare	No	Yes	Yes	Yes
Fixed-effects				
Pickup Date	Yes	Yes	Yes	Yes
Pickup Time			Yes	Yes
Pickup Borough				Yes
Fit statistics				
Observations	370	3,305	72,726	271,207
R^2	0.59331	0.73931	0.74646	0.68301
Within R^2	0.33694	0.73602	0.72696	0.60234

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 8: Diff-in-Diff Comparing E-Hailed Yellow Taxi Ridership and E-hailed Green Taxi Ridership. This Table is for NYC (Except for Places Where Green Taxis Don't Operate i.e. Below East 96th Street and West 110th Street in Manhattan) - Pre-post Analysis Investigating the Impacts of Automatically Matching UberX requests with Yellow Taxis in 2023

Dependent Variable:	ln(Count)		
Model:	(1)	(2)	(3)
Variables			
Yellow	1.105***	1.047***	0.6622***
	(0.0459)	(0.0539)	(0.0534)
Yellow × Post	0.1844*	0.2397**	0.1343**
	(0.0718)	(0.0750)	(0.0462)
Fixed-effects			
Fare	No	Yes	Yes
Fixed-effects			
Pickup Date	Yes	Yes	Yes
Pickup Time			Yes
Fit statistics			
Observations	370	1,556	22,763
R^2	0.87152	0.76082	0.39341
Within R^2	0.85970	0.74997	0.36079

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 9: Differences-in-Differences Regression Table Comparing Conventional Taxi Ridership with Car-hail Ridership. This Table is for Chicago - Pre-post Analysis of the Integration of Conventional Taxis on Uber in 2024

Dependent Variable:	ln(Count)			
Model:	(1)	(2)	(3)	(4)
Variables				
treatment	-4.088***	-4.685***	-4.155***	-1.935***
	(0.0558)	(0.0474)	(0.0588)	(0.0533)
treatment × post	0.2237***	0.2319***	0.1879***	0.0602***
	(0.0659)	(0.0539)	(0.0151)	(0.0078)
Control				
Pickup Date	No	Yes	Yes	Yes
Fixed-effects				
Pickup Date	Yes	Yes	Yes	Yes
Pickup Time			Yes	Yes
Pickup Neighborhood				Yes
Fit statistics				
Observations	2,115	282	47,551	5,097,970
R^2	0.89897	0.99651	0.84390	0.53579
Within R^2	0.89798	0.99648	0.83907	0.37202

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

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