The Effect of Congestion Surcharge Policy on Taxi Tipping Behavior: Evidence from New York City

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Abstract

This paper examines how New York City's congestion surcharge affects passenger tipping behavior in yellow and green taxis. Using trip-level data from NYC Open Data, I construct tip ratios and apply a Difference-in-Differences framework comparing trips that enter or leave the congestion zone to those occurring entirely outside it, while controlling for detailed trip characteristics, origin–destination pairs, and time fixed effects. The results show that the tip percentages increase by 3.1–3.9 percentage points for yellow taxis and 2.3–2.9 percentage points for green taxis after the introduction of the policy. The estimates remain positive and statistically significant across a wide range of heterogeneous trip characteristics. These patterns suggest that when congestion-related costs and delays are more salient, passengers are more likely to compensate drivers through higher tips. Overall, the findings suggest that tipping serves as an important behavioral margin of adjustment, showing that the effects of visible, policy-induced charges can extend beyond posted prices and shape discretionary payments.

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1 Introduction

Starting February 1, 2019, New York City adopted a congestion surcharge for taxi and for-hire vehicle (FHV) trips in Manhattan below 96th Street. Nonshared taxi (yellow taxi) trips incur a $2.50 surcharge, while nonshared FHV trips (including Uber, Lyft, and green taxi) are charged $2.75. Shared rides have a reduced $0.75 surcharge. The surcharge must be paid by passengers and cannot be deducted from driver earnings.

This study investigates how passengers adjust their tipping behavior in response to the implementation of New York City's congestion surcharge, a policy aimed at reducing traffic in Manhattan by charging an additional fee for trips entering the designated congestion zone. The analysis quantifies the extent to which the surcharge is offset through changes in tips and examines heterogeneity across taxi types, given the different surcharge amounts ($2.50 for yellow taxis and $2.75 for green taxis) and service areas.

To conduct this analysis, I use detailed trip-level data from NYC Open Data, which provides publicly available records for both yellow and green taxis. The dataset includes fields such as pick-up and drop-off dates and times, trip distances, fare amounts, tip amounts, congestion surcharge amounts, pickup and drop-off location IDs, and rate code IDs. These variables allow the construction of the tip ratio, calculation of trip speed, classification of origin–destination pairs, and assignment of trips to congestion and non-congestion zones, enabling a causal analysis of tipping responses to the policy.

Empirically, I employ a Difference-in-Differences (DiD) framework comparing trips that enter or leave the congestion zone (treated trips) to trips with both pickup and drop-off locations outside the zone (control trips). I also explore heterogeneity across fare levels, trip speeds, negotiation status, airport trips, and holidays to better understand the mechanisms underlying observed tipping responses.

The results show that tipping increases significantly in congestion areas following the introduction of the surcharge. Tip percentages rise by approximately 3.1–3.9 percentage

points for yellow taxis and 2.3–2.9 percentage points for green taxis after the policy change. Heterogeneity analyses reveal that the strongest responses occur for slow, negotiated, and non-airport trips. These patterns suggest that when congestion-related costs and delays are more salient, passengers are more likely to compensate drivers through higher tips. The estimates of the event study support the assumption of parallel trends and demonstrate that tipping increases immediately after the introduction of the policy and persists over time.

This study contributes to the literature in several important ways. First, it provides one of the earliest empirical evaluations of how congestion pricing affects tipping behavior in a large urban taxi market. Second, it documents substantial heterogeneity in passenger responses across taxi types and trip characteristics, highlighting how congestion salience, fare size, and service flexibility shape behavioral adjustments. Building on the tax salience framework of Alm (1988), the analysis shows that when the New York City congestion surcharge appears as a visible, itemized charge, passengers respond not by fully absorbing the additional cost but by reducing discretionary tipping, effectively shifting part of the policy burden onto drivers. This pattern suggests that gratuities can serve as a margin of tax incidence in settings where worker compensation depends heavily on discretionary payments. More broadly, the findings provide insight into consumer responses to policy-induced cost shocks and underscore the importance of charge visibility for policy design in markets where behavioral norms play a central role.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 outlines the empirical methodology. Section 5 presents the main results, Section 6 reports robustness checks, and Section 7 discusses limitations and concludes.

2 Literature Review and Contribution

Tipping is a common but puzzling economic practice. It is a voluntary payment made by consumers after a service is provided. In many cases, tips cover a large share of worker income but sometimes, less correlated with service quality. The literature on tipping approaches the topic from several angles: psychology (norms, guilt, and social approval), behavioral economics (defaults and focal points), labor and firm strategy (wage structures, monitoring, and tip capture), and empirical field or experimental studies across restaurants, taxis, and other service contexts.

2.1 Congestion Surcharge and Urban Transportation

Many studies find that deregulation and expansion of the infrastructure make congestion worse. Khulbe et al. (2020) documents that New York City's congestion surcharge altered travel behavior. The taxi deregulation policy caused a substantial slowdown of 8-9% in New York City (Mangrum and Molnar, 2017), while increasing road capacity leads to a proportional rise in traffic, which confirms the "fundamental law of highway congestion" (Duranton and Turner, 2011). Alternatively, building subway lines increases rush hour road speeds on nearby roads, particularly those that were initially more congested (Gu et al., 2021). Similarly, using evidence from the UAE, Abulibdeh (2018) estimates that high-occupancy toll lanes and cordon pricing can reduce congestion and travelers across socioeconomic groups are willing to pay for HOT lanes to avoid congestion, especially under worse trip conditions. In this context, the New York City congestion price policy was updated in January 2025. This policy became the first city in the United States to introduce a fee for vehicles entering its central business district (CBD).With the adoption of this new congestion pricing policy, it improved traffic speeds by 16 percent and reduced travel times by 8 percent in the central business district (Cook et al., 2025).

2.2 Tipping Norms and Psychological Motivations

Tipping behavior is not strictly based on rational calculation; rather, it reflects conformity to social norms and expectations. Some people tip to show appreciation for good service, but tipping habits really depend on where you are and what the local culture is. For example, tipping has not taken root in Japan, suggesting that without supportive social norms, tipping loses its intended economic function (Flath, 2012).

In places where tipping is the norm, people often tip more because it's just what everyone does. During the holiday season, people tend to tip significantly more, reflecting the influence of the "holiday generosity norm". Even individuals who normally tip less increase their tips during this time, while generous tippers become even more generous, driven by expectations of widespread prosocial behavior (Greenberg, 2014).

How much people tip can also depend on who they are and the situation they're in. Tourists and theatergoers tend to tip more than locals and those not attending shows, and tourists who attend theater performances are especially generous (Neto et al., 2019). Motivations behind tipping include future service expectations, reciprocity, altruism, and generally favorable attitudes toward the practice. While national norms do not directly affect why people tip, they do shape how much influence personal attitudes have on tipping behavior (Lynn and Brewster, 2020).

New technology is also changing how people tip. For example, research on AI-driven dynamic pricing reveals that a 1% increase in AI-adjusted fares leads to a 0.209% decrease in the tip-to-fare ratio, suggesting that customers may view higher prices, especially those set by algorithms as reducing the need or willingness to tip (Liu et al., 2024).

Even when future interactions are unlikely, such as in the case of tipping taxi drivers, many people still comply with the norm (Azar, 2004). Importantly, research consistently shows that tips are only weakly correlated with service quality(Conlin et al., 2003; Lynn et al., 2012), suggesting that psychological and social drivers outweigh rational efficiency

motives.

2.3 Tipping, Labor Markets, and Firm Strategy

Besides psychology, tipping has major implications for labor economics and firm strategy. In the United States, millions of workers rely on tips as a large share of their income, which is worth billions of dollars annually. Employers sometimes adapt wage structures to capture tip-generated rents through mechanisms like tip pooling, expanding the number of tipped workers, or assigning extra tasks (Azar, 2003). Empirical studies also examine how tipped minimum wages affect employment and worker outcomes (Wessels, 1997). Schwartz (1997) simulates markets with both monopolist and competitive firms and show that tipping increases profitability when consumer segments differ in demand and tipping behavior, while also potentially serving as a low-cost mechanism for performance monitoring, consumer evaluation, and price discrimination. These dynamics show how tipping interacts with both firm incentives and broader labor market regulations.

2.4 Behavioral Economics and Empirical Evidence on Tipping

Many studies highlight how behavioral nudges, social norms, and situational factors shape tipping outcomes across service settings. Defaults in digital payment systems exert a powerful influence: higher suggested tips increase average tips, though they also raise the probability of passengers leaving no tip at all (Haggag and Paci, 2014). Field studies in New York City taxis confirm that default options and payment interface design strongly affect behavior, with higher defaults reducing compliance but still raising average tips (Hoover, 2022). Similarly, passengers are more likely to select integer suggestions on tip menus, which act as focal points and boost total tips (Cross and Zhang, 2024) and the bill amount and passenger amount will also determine the tip amount (Bodvarsson and Gibson, 1997)

3 Data

All taxi trip data are publicly available through NYC Open Data, a free resource provided by New York City agencies and partners. New York City Taxi and Limousine Commission (2025) provides detailed trip record data for both yellow and green taxis. Starting in 2009, this dataset includes fields such as pick-up and drop-off dates and times, trip distances, fare amounts, and tip amounts.

From the dataset, I extract the following key variables used in the analysis: pick-up and drop-off location dates and times, trip distances, fare amount, total fare amounts, tip amounts, congestion surcharge amounts, pickup and drop-off location IDs (to assign trips to congestion or non-congestion areas), and rate code IDs (to identify different types of trips). These variables allow the construction of the tip ratio, average speed, origin–destination pairs, and distance bins, as it will be described in the Methodology section.

The analysis includes trips subject to the congestion surcharge across different rates (0, 0.75, and 2.75). For green taxis, the full sample consists of 8,029,757 trips, which decreases slightly to 8,029,687 trips after excluding shared rides (corresponding to the 0.75 surcharge). For yellow taxis, the full sample contains 135,877,162 trips, which reduces to 135,611,756 trips once shared rides are removed. Excluding shared rides ensures that the analysis focuses on single-rider trips, providing a cleaner comparison of tipping behavior across congestion surcharge levels.

Table 1 and Table 2 report summary statistics separately for yellow and green taxi trips. Yellow taxis exhibit a substantially higher average tip ratio (16.3 percent) than green taxis (11.0 percent), consistent with differences in service areas and trip characteristics. Yellow taxi trips are far more likely to involve the congestion zone, with 93 percent of trips classified as congested on average, compared to only 19 percent for green taxis. Green taxi trips are longer in duration on average and slightly faster, reflecting their greater concentration outside Manhattan and lower exposure to central business district traffic. Airport trips are common

among yellow taxis but rare among green taxis, while negotiated-fare trips occur almost exclusively in the green taxi market.

4 Methodology

4.1 Identification Strategy

Figure 1 shows the congestion surcharge area, and Figure 2 shows the yellow taxi and green taxi service areas. In New York City, yellow taxis can pick up passengers anywhere in NYC but are primarily found in Manhattan below 96th Street and some airport trips. Green taxis serve the outer area in NYC (Bronx, Brooklyn, Queens, Staten Island) and Upper Manhattan.

To identify the effect of the congestion surcharge on consumer tipping behavior, I define treated and control groups based on the location of the trip relative to the congestion area. The control groups include trips where both the pickup and drop-off locations are outside the congestion area, as these trips were not subject to the congestion surcharge before or after the 2019 policy change. The treated group includes trips where either the pickup or drop-off locations are within the congestion area (Or both). These trips did not receive a congestion fee before 2019, but were subject to a surcharge after the policy change, as indicated in the column "congestion surcharge" of the data set.

The same idea can also be applied to the green taxi group. Additionally, I can compare horizontally by analyzing how consumer tipping behavior varies for trips that include the congestion surcharge in both yellow taxis and green taxis, given that the green taxi surcharge is 25 cents higher than that of yellow taxis. Figure 3 shows the taxi zone map and the assignment of the treated and control groups.

4.2 Sample Period

Even though the congestion surcharge policy was announced to take effect on January 1, 2019, it was not actually implemented until February 1 2019. I explicitly exclude January 2019 from the analysis because passengers may have anticipated the upcoming congestion surcharge during that month. Therefore, the final sample includes pre-policy observations from January 2018 through December 2018 and post-policy observations from February 2019 through December 2019. Additionally, I only include card transactions for fare payments, since the dataset is only recorded for credit card tips. In most cases, people typically tip by credit card when they also pay the fare using a credit card. During our research period, taxi fare in New York City begin at a base rate of $2.50, and to reduce measurement error, the data are further filtered to include only trips with a total fare of at least $2.50.

4.3 Definition of Variables

4.3.1 Tip Ratio

The percentage of tipping is used as the outcome variable to capture the tipping behavior of consumers. To define the tip ratio, I calculate the tip percentage for each trip as the tip amount divided by the total fare amount minus the congestion surcharge, multiplied by 100.

$$\text{Tip Ratio} = \frac{\text{Tip Amount}}{\text{Total Fare Amount-Congestion Surcharge}} * 100$$

4.3.2 Average Speed

The tip ratio may be closely related to how smooth the trip is. To construct an independent variable capturing average speed, I calculate trip duration as the difference between pickup time and drop-off time. Using trip distance, I then compute average speed by dividing distance by trip duration.

4.3.3 Origin–destination Pair

I construct an origin–destination pair fixed effects which is defined by the combination of pickup and drop-off location IDs and represents a specific route between two locations. This grouping allows trips sharing the same origin and destination to be analyzed together, capturing route-level characteristics that are stable over time.

4.3.4 Day Of Week

The day of the week indicates the calendar day on which a trip takes place and is used to classify trips into distinct weekday categories. This grouping captures recurring weekly patterns in travel demand and behavior. Figure 4 and Figure 5 show the average tip ratio by day of the week for yellow and green taxis, respectively. Both figures reveal clear day-of-week patterns in tipping behavior, with systematic differences between weekdays and weekends.

4.3.5 Distance Bin

To capture spatial variation in exposure to New York City's congestion surcharge and systematic differences in tipping behavior by trip length, I construct fixed effects in the distance-bin based on the trip distance. Distances are grouped into five mutually exclusive bins: 0–1, 1–2, 2–5, 5–10, and 10+ miles. As shown in Figure 6 and Figure 7, average tip ratios decline with trip distance for both yellow and green taxis, with shorter trips exhibiting substantially higher tipping rates than longer trips. This strong distance gradient motivates the inclusion of distance-bin fixed effects to flexibly control for heterogeneity in tipping behavior correlated with trip length and spatial exposure.

4.4 Empirical Strategy

To analyze the impact of the congestion surcharge on consumer tipping behavior, I employ the Difference-in-Differences (DID) approach and estimate the following model for both

yellow taxi and green taxi:

$$Tip\%_{it} = \beta_0 + \beta_1 Congestion_i + \beta_2 Post2019_t + \beta_3 (Congestion_i \times Post2019_t) + X_{it}\gamma + FE_{it} + \varepsilon_{it} \quad (1)$$

Where: The dependent variable, $Tip\%_{it}$, represents the percentage of tipping for the trip i at time t. The variable $Congestion_i$ is a binary indicator equal to 1 if the trip occurred within the congestion zone and 0 otherwise. $Post2019_t$ is a binary indicator equal to 1 for trips that occur after the implementation of the congestion surcharge in 2019 and 0 otherwise. The interaction term $Congestion_i \times Post2019_t$ captures the difference-in-differences effect of the congestion pricing policy on tipping behavior.

The vector $\mathbf{X}_{it}$ includes time-varying trip-level control variables: trip duration, passenger count, toll amount, and average speed. The term FE_{it} is the vector of all the fix effects in the model. The specification includes different combinations of pick up–drop off pair fixed effects, day fixed effects, pickup-hour fixed effects, distance-bin fixed effects, and month fixed effects. ε_{it} is the error term capturing unobserved determinants of tipping behavior.

The coefficient β_1 represents the baseline effect of being in the congestion area on tipping behavior. β_2 captures the general effect of the post-2019 policy on tipping behavior. β_3 is the difference-in-differences estimate measuring how tipping behavior changes due to the congestion surcharge.

4.5 Trip Heterogeneity

To investigate whether the impact of the congestion surcharge on tipping behavior varies across different types of taxi trips, I estimate a set of separate heterogeneity models stratified by trip characteristics. I define cheap trips as rides with a total fare at or below the sample median and expensive trips as rides with total fares exceeding the 90th percentile of the fare distribution. I further classify trips by traffic conditions, defining slow trips as those

with average speed at or below the median and fast trips as those with speed above the 90th percentile. Additionally, using different rate code ID, I also include negotiated trips and airport trips, corresponding to JFK or Newark airports. Lastly, I also include holiday trips, identified using a manually constructed holiday calendar covering major U.S. holidays and adjacent peak travel days. For each subsample, I re-estimate the baseline difference-in-differences specification using identical controls, fixed effects, and clustering, allowing the congestion surcharge effect on the tip ratio to vary across distinct trip types.

4.6 Assumption

One of the important assumptions of the difference-in-differences framework is that, before the treated applies, the treated and control groups would have followed parallel trends. To test this, I plot and compare the monthly average tip ratios in congestion and non-congestion areas between January 2018 and December 2019. Figure 6 and Figure 7 present the monthly average tip ratios for both yellow taxi and green taxi. These trends appear visually parallel before the implementation of the congestion surcharge in February 2019 (black vertical line), which satisfies the assumption of parallel trends. Consistent with this pattern, the average tip amount for treated yellow trips increased from \$2.60 to \$3.01 (a \$0.41 rise), while the control group's tip amount increased from \$3.62 to \$4.15 (a \$0.54 rise).

In addition, as shown in Table 3 and Table 4, the mean tip ratios for both yellow and green taxis increased following the 2019 congestion surcharge. For yellow taxis, the treated group rose from 15.42% before the policy to 18.07% after, a statistically significant increase of 2.65 percentage points, while the control group decreased from 14.35% to 12.90%, a decline of 1.45 points.

For green taxis, the treated group increased from 12.71% to 16.54% (+3.83 points), and the control group also showed a smaller but significant rise from 10.18% to 10.51% (+0.33 points). Tip amounts for green taxis display a similar pattern: treated trips increased from \$2.84 to \$3.64 (a \$0.80 rise), whereas the control group remained essentially unchanged,

moving from \$1.54 to \$1.52. These results indicate that the congestion surcharge led to higher tipping primarily in the treated trips, with the largest effect observed for yellow taxis.

4.7 Event Study

I include an event study by examining the coefficients for multiple time periods relative to the policy change.

$$\text{Tip}\%_{it} = \sum_{\substack{t=-12 \\ t\neq 0}}^{11} \beta_t \cdot (\text{Congestion}_{it} \times \mathbf{1}[\text{Month} = t]) + \mathbf{X}_{it}\gamma + FE_{it} + \varepsilon_{it} \tag{2}$$

The summation runs from January 2018 ($t = -12$) to December 2019 ($t = 11$), excluding February 2019 ($t = 0$) as the reference month[1]. Each coefficient β_t captures the treated effect at month t relative to February 2019. The coefficients trace the dynamic treated effects relative to the month immediately preceding the policy implementation, allowing for a transparent assessment of pre-trends and the evolution of treated effects following policy onset.

5 Results

5.1 Baseline Results

Table 5 presents the results of the regression for the yellow taxi using four different combinations of fixed effects. The regression results show that the baseline effect of trips being in the congestion area were significantly positive to the tip percentage across all the models. The tip percentages are typically around 0.84 to 1.99 percentage points higher. This suggests that, consumers may appreciate the drivers more for their effort driving through the congestion area and dealing with the potential delays that caused by the traffic. In addition, the

[1] As I mentioned earlier, January 2019 is excluded

tip percentages decrease and the statistically significant effect on tipping across all models after the policy change.

However, the interaction term, Congestion × Post2019, reveals some interesting results. Following the implementation of the congestion surcharge, tip percentages increase significantly in all specifications, with estimates ranging from approximately 3.1 to 3.9 percentage points, and all coefficients are statistically significant at the 1% level. This suggests that, contrary to concerns about fare burden crowding out tips, passengers in congestion areas appear to compensate drivers by tipping more after the surcharge was introduced.

In terms of green taxis, the regression results from Table 6 show larger effects compared to yellow taxis. The baseline effect of trips occurring in the congestion area indicates that tip ratios are approximately 2.6 to 4.6 percentage points higher, which is a stronger effect than what we observe for yellow taxis. In addition, following the policy change, tip ratios increase further and remain statistically significant across all specifications.

The interaction term, Congestion × Post2019, also shows a positive and statistically significant effect in all models, with estimates ranging from approximately 2.3 to 2.9 percentage points. This suggests that after the implementation of the congestion surcharge, passengers using green taxis in congestion areas tend to tip more, rather than less. Compared to yellow taxis, this response appears less stronger, indicating that yellow taxi riders may be more responsive to the surcharge or more willing to compensate drivers through higher tips following the policy change.

5.2 Heterogeneous Results

The heterogeneous DiD results reveal substantial variation in tipping responses to the congestion surcharge across trip characteristics and taxi types, but a consistent pattern emerges: the interaction term Congestion × Post2019 is positive and statistically significant in nearly all specifications.

When splitting trips by price, both cheap (Table 7 and Table 8) and expensive trips

(Table 9 and Table 10) show increased tipping in congestion areas after the policy change. For yellow taxis, the interaction effects are larger for cheap trips (approximately 3.2–3.9 percentage points) than for expensive trips (about 1.1–2.1 percentage points), suggesting that riders on lower-fare trips adjust tipping behavior more strongly in response to the surcharge. For green taxis, the interaction effects are positive but generally smaller in magnitude for cheap trips, while the effects for expensive trips are larger (2.7–5.1 percentage points).

Results by trip speed indicate that tipping responses are strongest for slow trips (Table 11 - Table 14). Both yellow and green taxis experience large and highly significant increases in tip ratios for slow trips in congestion areas after 2019, with interaction effects exceeding 3 percentage points for yellow taxis and around 2.5–2.8 percentage points for green taxis. Fast trips also exhibit positive and statistically significant interaction effects, though the magnitudes are more moderate. This smaller response is likely because faster trips are less affected by congestion-related delays, making the surcharge less noticeable and reducing the incentive for passengers to adjust their tipping behavior upward.

Negotiation (Table 15 and Table 16), airport (Table 17 and Table 18), and holiday trips (Table 19 and Table 20) also exhibit meaningful heterogeneity in tipping responses. Negotiated trips show some of the largest interaction effects for green taxis, with large and statistically significant coefficients, suggesting that when fares are more flexible or salient, passengers are more likely to adjust tipping behavior upward after the policy change. In contrast, airport trips display positive but noticeably smaller interaction effects, particularly for yellow taxis, which likely reflects more standardized fares and established tipping norms that leave less room for behavioral adjustment. Holiday trips, continue to show positive and significant interaction effects across both taxi types, indicating that the increase in tipping in congestion areas persists even during periods of atypical travel demand.

Overall, these heterogeneous results suggest that the congestion surcharge is associated with higher tipping in congestion areas after implementation, with the strongest responses occurring for slow, cheaper, negotiated, and non-airport trips. The findings are consistent

with the idea that when congestion costs are more salient or perceived as burdensome for drivers, passengers partially offset these costs through increased tipping behavior.

5.3 Event Study Results

Figure 8 and Figure 9 present the event study estimates of the effect of the congestion surcharge on tip ratios for yellow and green taxis, respectively. In the months prior to the policy implementation in February 2019, the estimated coefficients remain relatively stable and close to zero, providing strong support for the parallel trends assumption. Following the introduction of the congestion surcharge, tip ratios for trips passing through congestion zones increase sharply for both taxi types, with effects that emerge immediately and persist over time. These dynamic patterns are consistent with the main DID results and highlight the immediate and sustained impact of the congestion pricing policy on tipping behavior.

6 Robustness Check

6.1 Redefine Tipping Ratio

First, I redress the definition of the tipping ratio. Since some consumers may tip based on the fare amount rather than the total fare, I redefine the variable "Tip Ratio" as the tip amount divided by the fare amount, multiplied by 100:

$$\text{Tip Ratio} = \frac{\text{Tip Amount}}{\text{Fare Amount}} * 100$$

Using this alternative definition, I rerun the baseline regression models for both yellow and green taxis. Table 21 and Table 22 present the corresponding robustness results.

For yellow taxis, while the interaction term remains positive across all specifications, it is generally not statistically significant under the redefined tipping measure. This suggests that yellow taxi tipping behavior may be more sensitive to how the tip ratio is constructed,

and that part of the baseline effect may operate through changes in the total fare rather than the base fare alone. For green taxis, the interaction term Congestion × Post2019 remains positive, statistically significant, and similar in magnitude to the baseline estimates, with coefficients ranging from approximately 3.5 to 4.3 percentage points across specifications. This indicates that the main findings for green taxis are robust to alternative definitions of the tipping ratio.

6.2 Redefine Congestion Zone

As an additional robustness check, I redefine the congestion zone to account for taxi zones that are only partially within the congestion pricing area. In particular, taxi Zone 43 and taxi Zone 238 are partially located inside the congestion zone but were excluded from the baseline specification. I reclassify these zones as part of the congestion area and re-estimate the baseline regressions for both yellow and green taxis. The results are reported in Table 23 and Table 24.

For yellow taxis, the interaction term Congestion × Post2019 remains positive, statistically significant, and similar in magnitude to the baseline estimates, ranging from approximately 2.8 to 3.8 percentage points across specifications. For green taxis, the interaction effects are likewise positive, statistically significant, and highly stable, with coefficients between 2.5 and 2.9 percentage points. These findings indicate that the main results are not sensitive to alternative definitions of the congestion zone and are robust to the inclusion of partially treated areas.

7 Discussion and Conclusions

This paper examines how a salient congestion surcharge affects tipping behavior in New York City taxis. Using trip-level data and a difference-in-differences framework, I find that tip percentages increase following the introduction of the surcharge, suggesting that riders

adjust discretionary payments in response to visible, policy-induced charges. These results highlight gratuities as an important margin of behavioral adjustment and contribute to the literature on tax salience and behavioral tax incidence.

Several limitations should be noted. First, although both pickup and drop-off locations may lie outside the congestion zone, some trips may still pass through the congestion area. This limitation arises from the lack of detailed route information in the data. An ideal dataset would include trip-level routing information, allowing for a more precise classification of trips that definitely cross versus those that do not cross the congestion zone. Second, tip amounts are recorded only for credit card payments. Cash tips are not observed, and riders may tip in cash even when paying by card. Because this measurement issue is systematic, it likely leads to attenuation bias in the estimated effects.

Future work could extend the analysis by examining spatial heterogeneity in tipping responses. In particular, tipping behavior may differ for trips that begin or end in high-activity areas, such as neighborhoods with dense concentrations of restaurants and theaters (Neto et al., 2019) or near major event venues like Madison Square Garden (Ge, 2018). Additional factors, including weather conditions, and public transit infrastructure such as subway expansions (Gu et al., 2021), may also shape riders' responses and help further isolate the mechanisms underlying the observed effects, as well as the impact of the new congestion surcharge policy on the CBD area (Cook et al., 2025).

Overall, the findings suggest that the behavioral incidence of congestion pricing extends beyond statutory payment and can influence complementary margins of consumer behavior. Accounting for salience and discretionary adjustments is therefore important for understanding the broader economic effects of congestion pricing and similar transportation policies.

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Figures and Tables

Figures

Figure 1. Congestion Surcharge Area

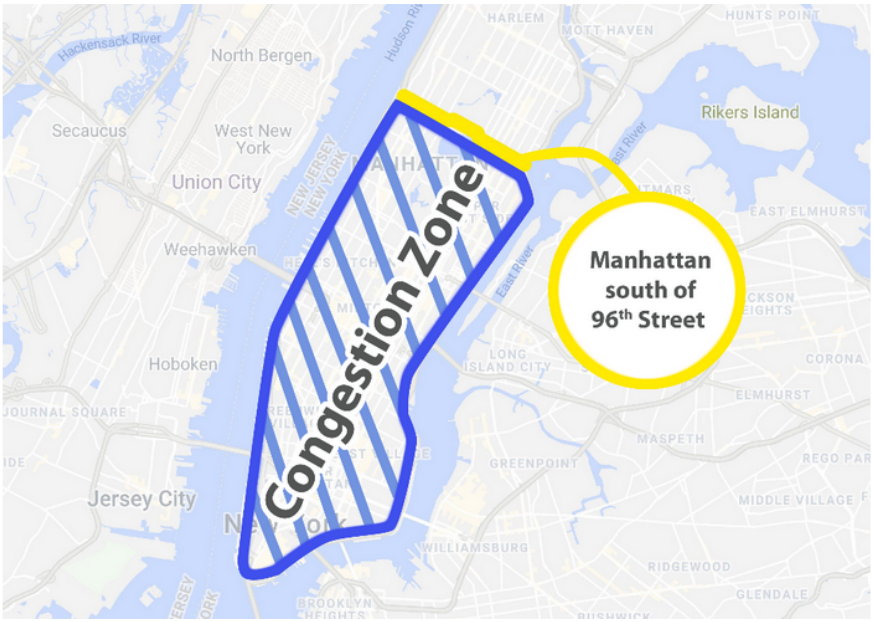


Figure 2. Yellow Taxi and Green Taxi Service Area



Figure 3. Taxi Zone Map

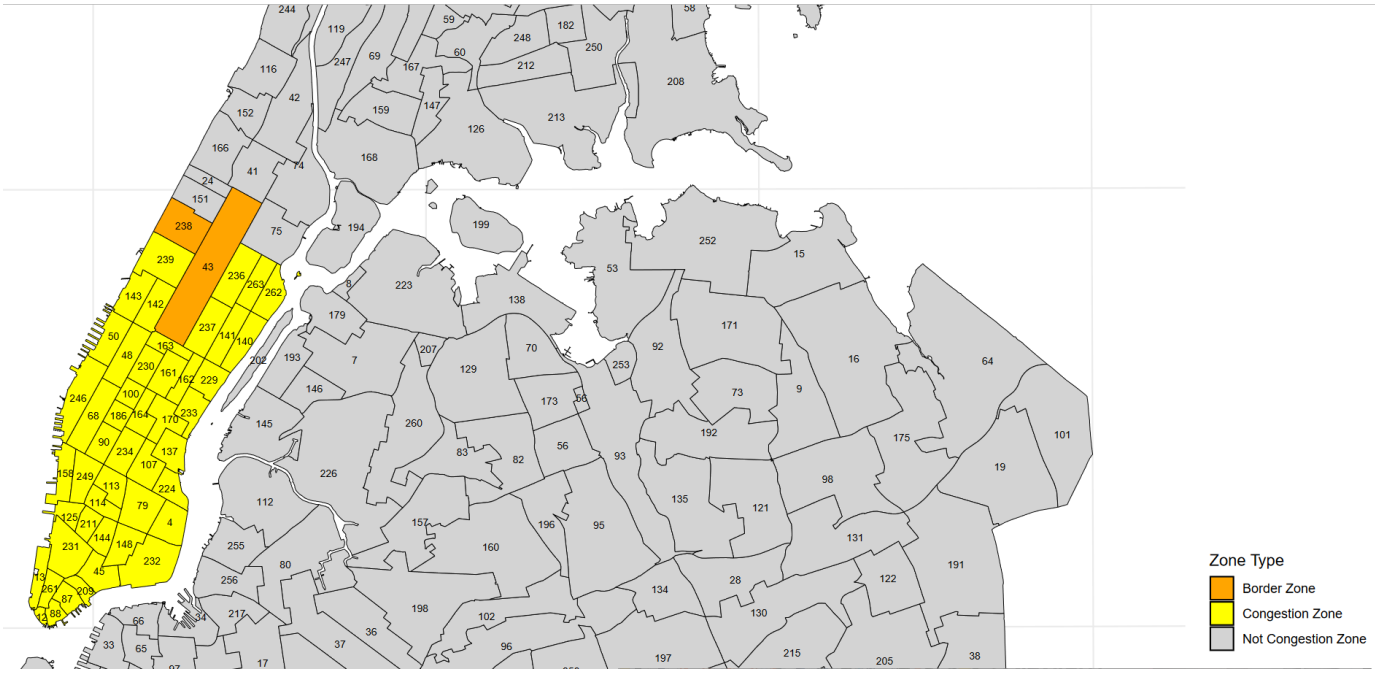


Figure 4. Tip Ratio By Yellow Taxi Day of the Week

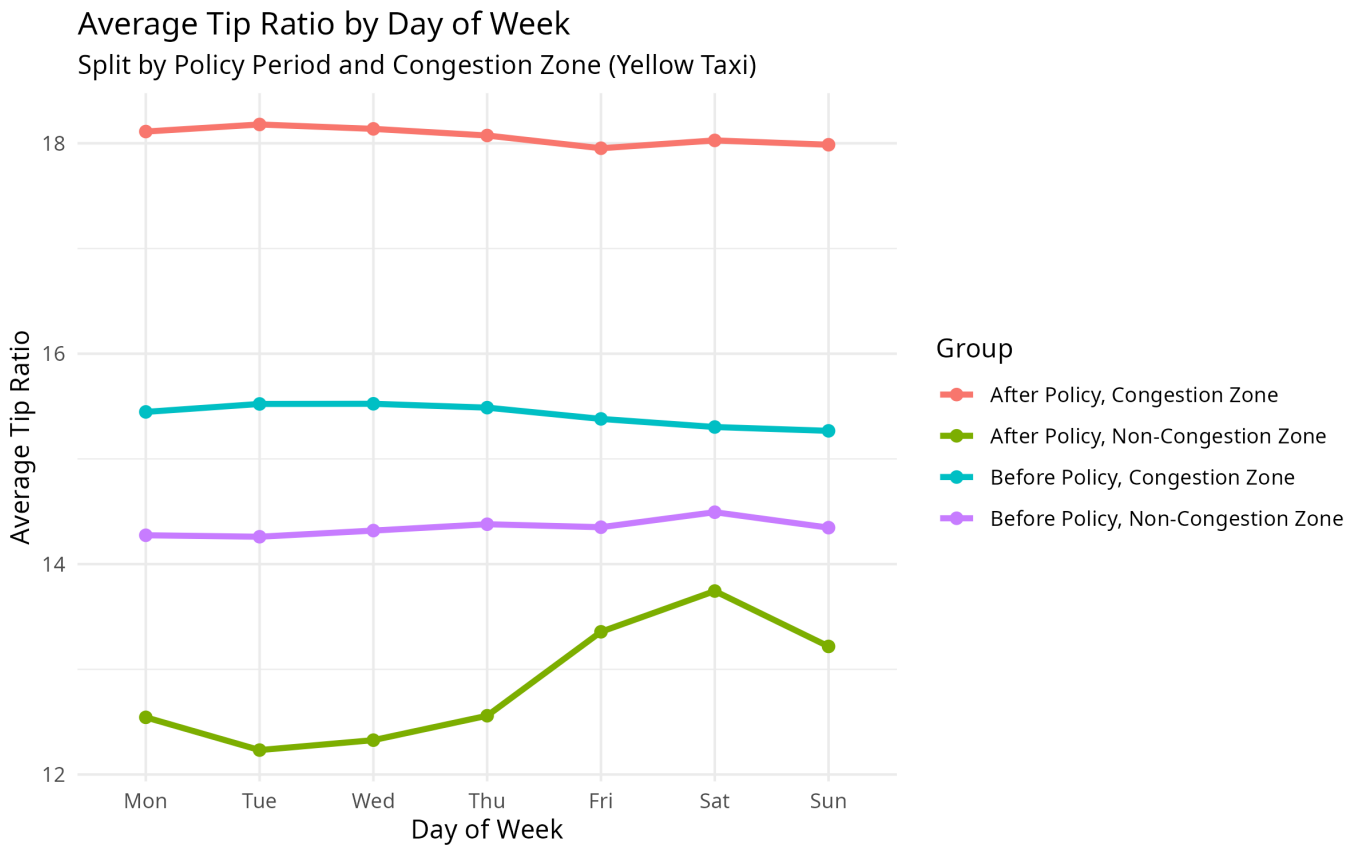


Figure 5. Tip Ratio By Green Taxi Day of the Week

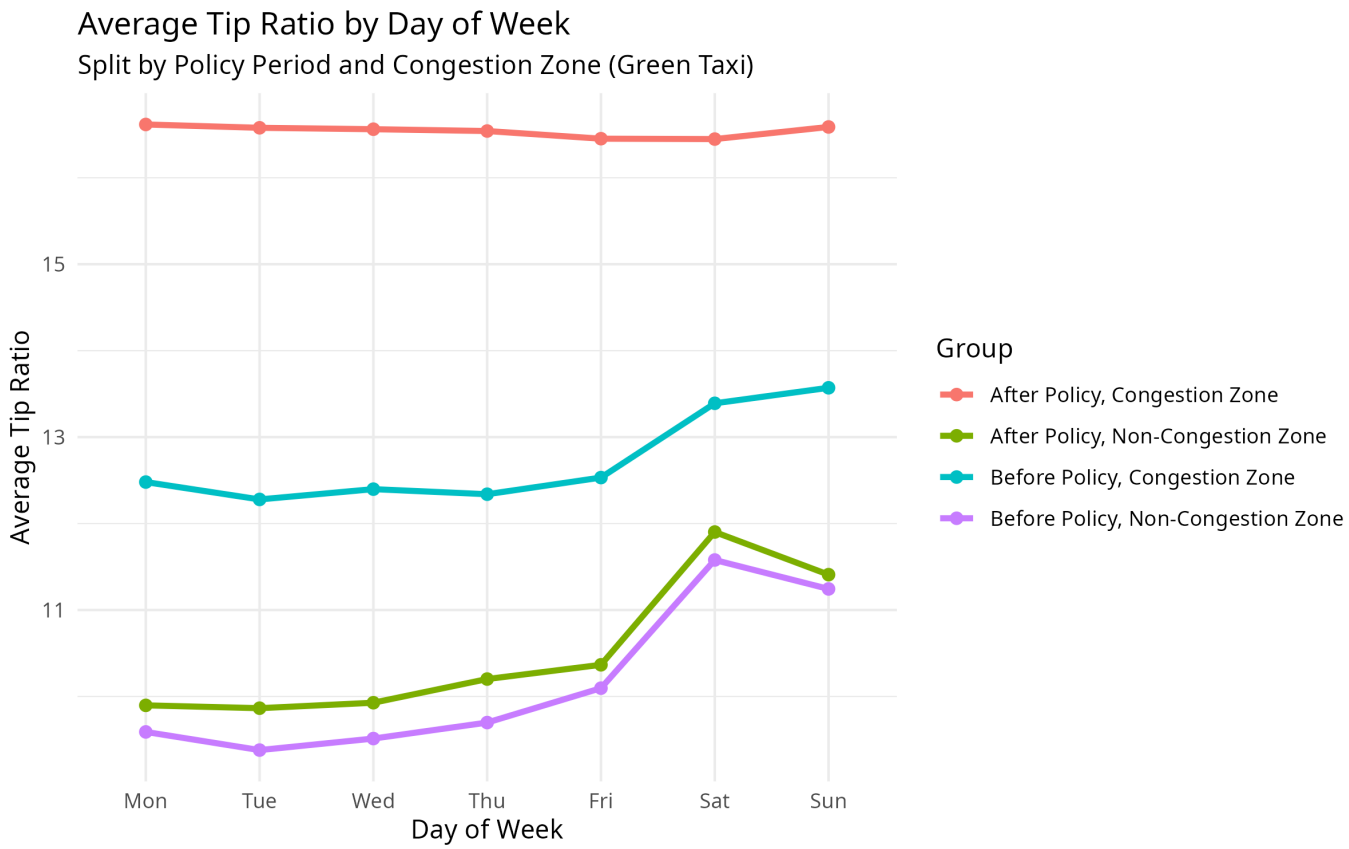


Figure 6. Yellow Taxi Tip Ratio By Distance Bin

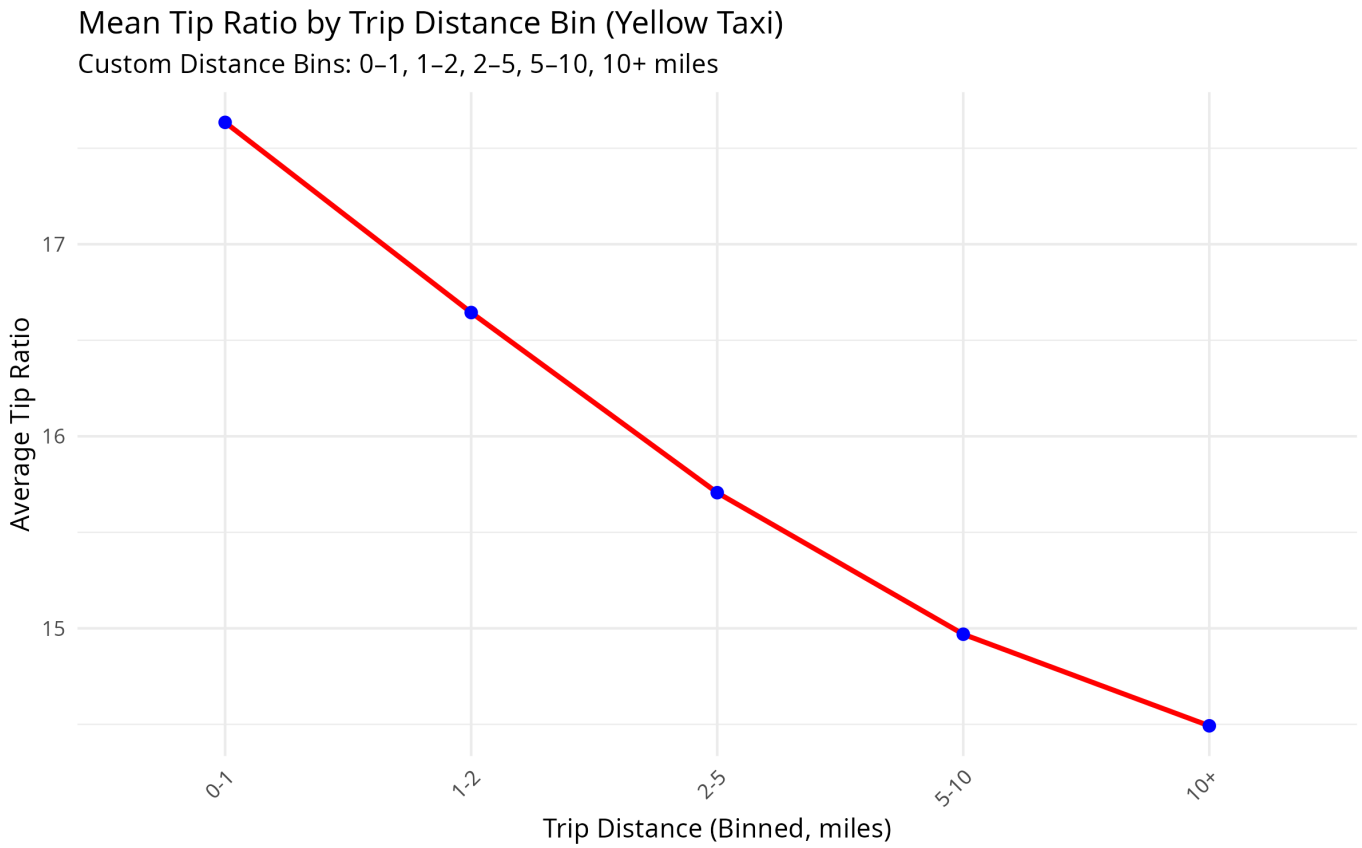


Figure 7. Green Taxi Tip Ratio By Distance Bin

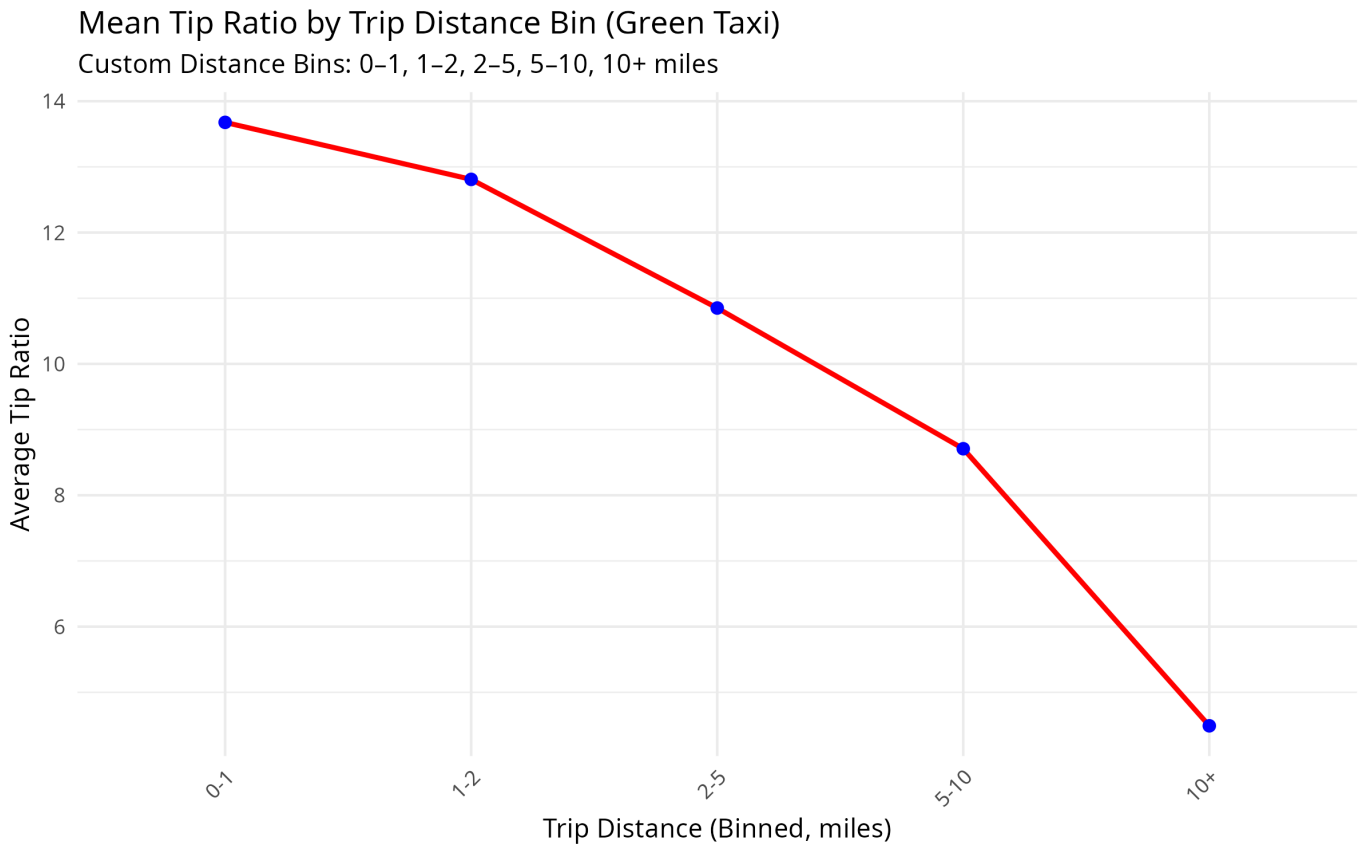


Figure 8. Parallel Trends for Yellow Taxi

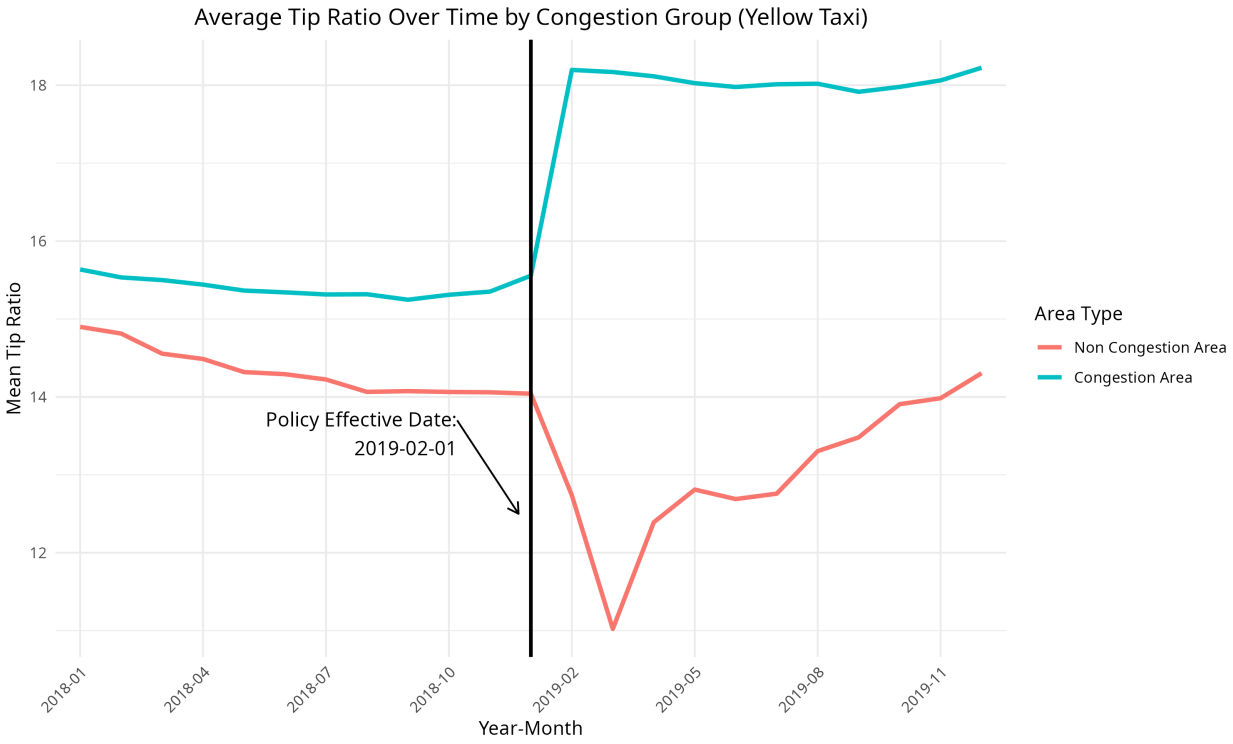


Figure 9. Parallel Trends for Green Taxi

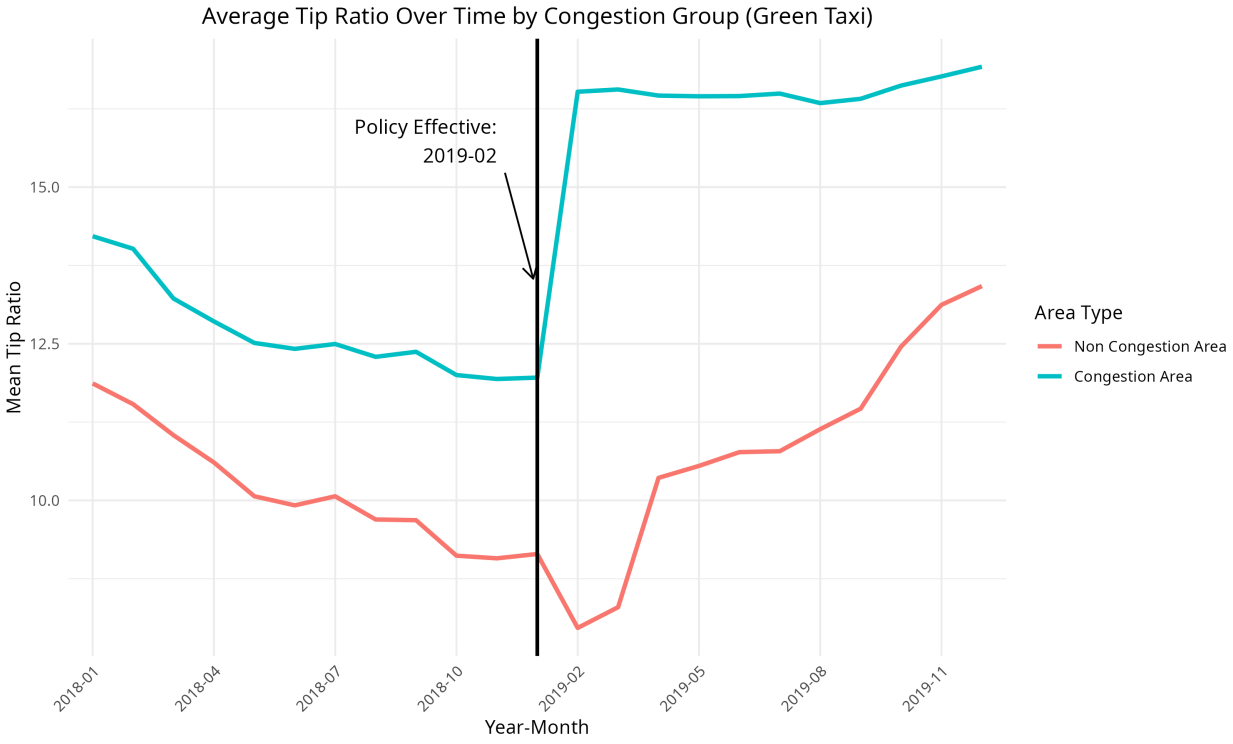


Figure 10. Event Study Tip Ratio Yellow Taxi

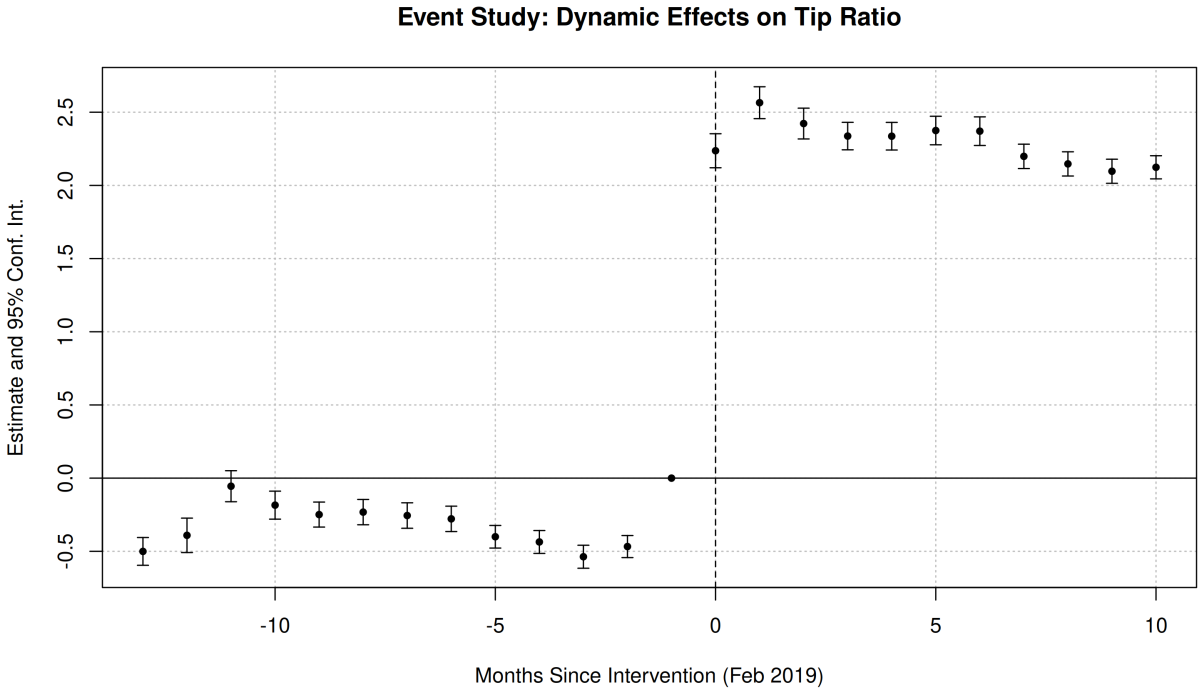
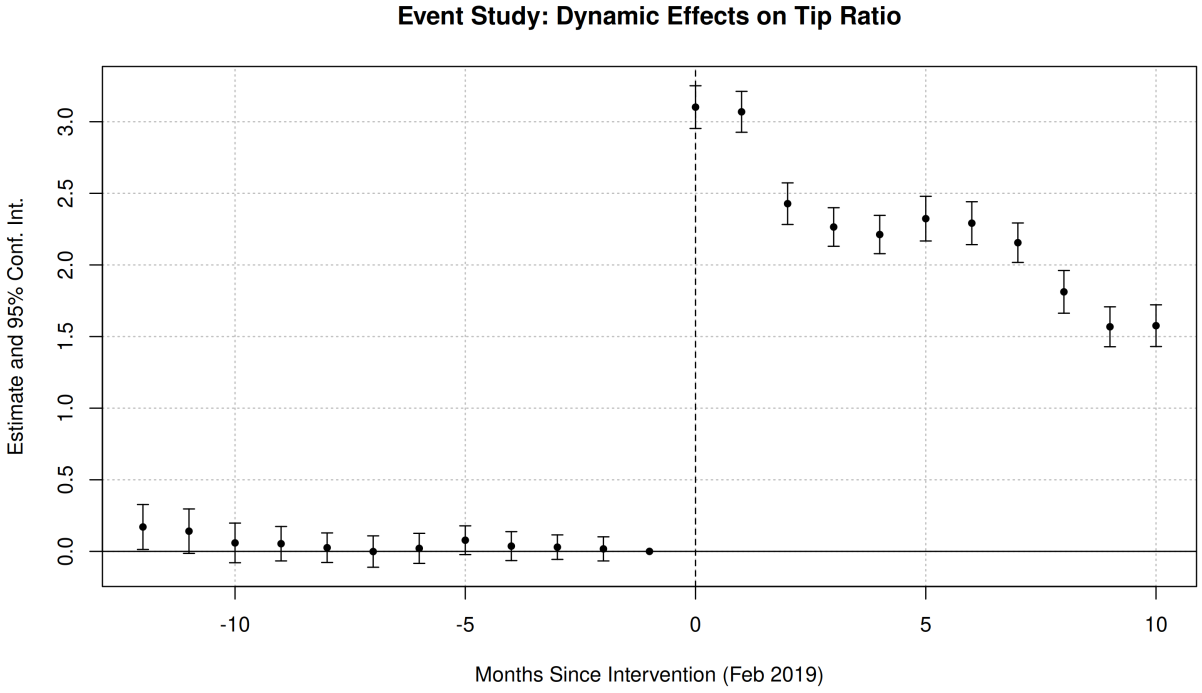


Figure 11. Event Study Tip Ratio Green Taxi



Tables

Table 1. Summary Statistics for Yellow Taxi

Variable	Min	Max	Mean	SD
Tip Ratio	0.00	99.94	16.33	5.76
Congestion	0.00	1.00	0.93	0.25
Post 2019	0.00	1.00	0.41	0.49
Cheap Trip	0.00	1.00	0.51	0.50
Expensive Trip	0.00	1.00	0.10	0.30
Slow Trip	0.00	1.00	0.50	0.50
Fast Trip	0.00	1.00	0.10	0.30
Negotiation	0.00	1.00	0.00	0.05
Airport Trip	0.00	1.00	0.03	0.16
Holiday Trip	0.00	1.00	0.05	0.21
Speed	0.00	250.21	0.19	0.12
Passenger Count	1.00	9.00	1.59	1.22
Trip Duration	1.00	1423.47	16.34	46.62
Tolls Amount	0.00	812.50	0.40	1.65

Table 2. Summary Statistics for Green Taxi

Variable	Min	Max	Mean	SD
Tip Ratio	0.00	97.98	11.03	8.71
Congestion	0.00	1.00	0.19	0.40
Post 2019	0.00	1.00	0.36	0.48
Cheap Trip	0.00	1.00	0.50	0.50
Expensive Trip	0.00	1.00	0.10	0.30
Slow Trip	0.00	1.00	0.50	0.50
Fast Trip	0.00	1.00	0.10	0.30
Negotiation	0.00	1.00	0.03	0.17
Airport Trip	0.00	1.00	0.00	0.05
Holiday Trip	0.00	1.00	0.05	0.22
Speed	0.00	126.01	0.21	0.13
Passenger Count	1.00	9.00	1.34	1.01
Trip Duration	1.00	1492.57	22.48	86.46
Tolls Amount	0.00	97.28	0.26	1.29

Table 3. Mean Tip Ratio and Tip Amount Before and After 2019 Policy (Yellow Taxis)

	Period	Treated Group	Control Group
Mean Tip Ratio	Before Feb 2019 Policy	15.420	14.348
	After Feb 2019 Policy	18.066	12.902
Difference		2.646^{***}	-1.446^{***}
Mean Tip Amount ($)	Before Feb 2019 Policy	2.60	3.62
	After Feb 2019 Policy	3.01	4.15
Difference		0.41^{***}	0.54^{***}
Number of Observations	Before Feb 2019 Policy	71,082,143	5,605,128
	After Feb 2019 Policy	50,162,061	3,399,816

$*p < 0.10,\ **p < 0.05,\ ***p < 0.01$

Table 4. Mean Tip Ratio and Tip Amount Before and After 2019 Policy (Green Taxis)

	Period	Treated Group	Control Group
Mean Tip Ratio	Before Feb 2019 Policy	12.712	10.176
	After Feb 2019 Policy	16.540	10.507
Difference		3.828^{***}	0.331^{***}
Mean Tip Amount ($)	Before Feb 2019 Policy	2.84	1.54
	After Feb 2019 Policy	3.64	1.52
Difference		0.80^{***}	-0.01^{***}
Number of Observations	Before Feb 2019 Policy	951,778	3,974,562
	After Feb 2019 Policy	530,331	2,190,780

$*p < 0.10,\ **p < 0.05,\ ***p < 0.01$

Table 5. Baseline DID Regression Results– Yellow Taxi

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	1.950***	1.989***	0.835***	1.983***
	(0.1886)	(0.1936)	(0.1732)	(0.1924)
Post2019	-0.500***	-0.498***	-1.252***	-0.497***
	(0.0438)	(0.0447)	(0.0840)	(0.0446)
Congestion × Post2019	3.087***	3.109***	3.905***	3.105***
	(0.0530)	(0.0538)	(0.0887)	(0.0538)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	130,249,148	130,249,148	130,249,148	130,249,148
R^2	0.1198	0.1220	0.0882	0.1228
Within R^2	0.0543	0.0535	0.0600	0.0535

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Baseline DID Regression Results – Green Taxi

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	2.598***	2.775***	4.617***	2.682***
	(0.2099)	(0.2211)	(0.1435)	(0.2089)
Post2019	0.2502***	0.2996***	0.3913***	0.3114***
	(0.0366)	(0.0372)	(0.0559)	(0.0363)
Congestion × Post2019	2.285***	2.345***	2.910***	2.294***
	(0.0822)	(0.0834)	(0.0819)	(0.0833)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	7,647,451	7,647,451	7,647,451	7,647,451
R^2	0.40200	0.39747	0.19531	0.40523
Within R^2	0.01267	0.01594	0.08381	0.01372

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Heterogeneous DiD Regression Results (Cheap Trips For Yellow Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	1.422***	1.472***	0.9892***	1.458***
	(0.1391)	(0.1482)	(0.2383)	(0.1473)
Post2019	-0.2741***	-0.2882***	-0.9571***	-0.2908***
	(0.0640)	(0.0644)	(0.1159)	(0.0646)
Congestion × Post2019	3.257***	3.187***	3.917***	3.185***
	(0.0787)	(0.0824)	(0.1275)	(0.0826)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	65,812,525	65,812,525	65,812,525	65,812,525
R^2	0.11920	0.12639	0.11181	0.12786
Within R^2	0.06414	0.06155	0.06941	0.06154

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Heterogeneous DiD Regression Results (Cheap Trips For Green Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	1.154***	1.489***	3.727***	1.484***
	(0.3718)	(0.4336)	(0.2680)	(0.4194)
Post2019	0.5015***	0.5388***	0.4581***	0.5522***
	(0.0433)	(0.0456)	(0.0661)	(0.0431)
Congestion × Post2019	1.443***	1.121*	1.060*	1.111*
	(0.5298)	(0.6265)	(0.5515)	(0.6131)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	3,848,061	3,848,061	3,848,061	3,848,061
R^2	0.29194	0.29548	0.11475	0.30229
Within R^2	0.00627	0.01036	0.02775	0.00812

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Heterogeneous DiD Regression Results (Expensive Trips For Yellow Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	2.119***	2.190***	0.8596***	2.143***
	(0.2189)	(0.2271)	(0.1288)	(0.2221)
Post2019	-0.1953***	-0.1989***	-0.9848***	-0.1942***
	(0.0541)	(0.0559)	(0.1043)	(0.0550)
Congestion × Post2019	1.123***	1.126***	2.125***	1.110***
	(0.0494)	(0.0513)	(0.1111)	(0.0502)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	12,937,218	12,937,218	12,937,218	12,937,218
R^2	0.20063	0.20455	0.05744	0.20629
Within R^2	0.01342	0.01430	0.02343	0.01295

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Heterogeneous DiD Regression Results (Expensive Trips For Green Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	1.731***	1.854***	1.232***	1.756***
	(0.0712)	(0.0740)	(0.2154)	(0.0709)
Post2019	-0.4859***	-0.4734***	-0.4175***	-0.4476***
	(0.0379)	(0.0411)	(0.0768)	(0.0400)
Congestion × Post2019	2.657***	2.823***	5.116***	2.616***
	(0.0774)	(0.0817)	(0.1404)	(0.0780)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	762,252	762,252	762,252	762,252
R^2	0.58435	0.58944	0.28131	0.59802
Within R^2	0.02166	0.03004	0.05867	0.02271

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Heterogeneous DiD Regression Results (Slow Trips For Yellow Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	2.024***	2.061***	1.206***	2.054***
	(0.2424)	(0.2491)	(0.4042)	(0.2473)
Post2019	-0.9353***	-0.9329***	-1.984***	-0.9368***
	(0.0930)	(0.0927)	(0.1572)	(0.0934)
Congestion × Post2019	3.686***	3.701***	4.787***	3.703***
	(0.0979)	(0.0975)	(0.1596)	(0.0982)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	65,125,512	65,125,512	65,125,512	65,125,512
R^2	0.10175	0.10446	0.08893	0.10578
Within R^2	0.06359	0.06263	0.06915	0.06327

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12. Heterogeneous DiD Regression Results (Slow Trips For Green Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	2.598***	2.801***	5.832***	2.772***
	(0.3341)	(0.3500)	(0.2322)	(0.3392)
Post2019	0.2197***	0.2961***	0.3751***	0.2938***
	(0.0459)	(0.0454)	(0.0644)	(0.0449)
Congestion × Post2019	2.456***	2.480***	2.791***	2.452***
	(0.1120)	(0.1133)	(0.1121)	(0.1133)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	3,823,728	3,823,728	3,823,728	3,823,728
R^2	0.38316	0.38252	0.18731	0.38848
Within R^2	0.01591	0.02306	0.09948	0.01898

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 13. Heterogeneous DiD Regression Results (Fast Trips For Yellow Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	1.540***	1.531***	0.6672***	1.540***
	(0.1916)	(0.1935)	(0.1112)	(0.1931)
Post2019	0.0351	0.0398	-0.4918***	0.0441
	(0.0379)	(0.0379)	(0.0718)	(0.0379)
Congestion × Post2019	1.535***	1.548***	2.167***	1.538***
	(0.0543)	(0.0548)	(0.0848)	(0.0546)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	13,024,857	13,024,857	13,024,857	13,024,857
R^2	0.16212	0.16176	0.05606	0.16292
Within R^2	0.02016	0.01907	0.03004	0.01920

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 14. Heterogeneous DiD Regression Results (Fast Trips For Green Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	2.133***	2.176***	2.607***	2.077***
	(0.1700)	(0.1777)	(0.1938)	(0.1696)
Post2019	0.2263***	0.3425***	0.5369***	0.3358***
	(0.0428)	(0.0430)	(0.0862)	(0.0425)
Congestion × Post2019	1.832***	1.818***	2.784***	1.780***
	(0.0858)	(0.0861)	(0.1364)	(0.0855)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	764,744	764,744	764,744	764,744
R^2	0.51569	0.51257	0.22394	0.51666
Within R^2	0.01479	0.01387	0.06980	0.01346

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 15. Heterogeneous DiD Regression Results (Negotiation Trips For Yellow Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	0.5342***	0.5146***	1.090*	0.5202***
	(0.0694)	(0.0708)	(0.5607)	(0.0695)
Post2019	0.0680	0.1485**	-0.3384	0.1304*
	(0.0537)	(0.0708)	(0.4914)	(0.0722)
Congestion × Post2019	1.360***	1.317***	4.134***	1.328***
	(0.0985)	(0.1029)	(0.5265)	(0.1031)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	323,283	323,283	323,283	323,283
R^2	0.48210	0.48223	0.23865	0.48290
Within R^2	0.01142	0.01111	0.10355	0.01125

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 16. Heterogeneous DiD Regression Results (Negotiation Trips For Green Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	0.7751***	0.7250***	0.9835***	0.6887***
	(0.0535)	(0.0522)	(0.0904)	(0.0518)
Post2019	0.0504*	0.7552***	1.544***	0.6804***
	(0.0268)	(0.0983)	(0.2368)	(0.0979)
Congestion × Post2019	3.605***	3.186***	4.785***	3.017***
	(0.2403)	(0.2479)	(0.3451)	(0.2435)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	237,112	237,112	237,112	237,112
R^2	0.52381	0.52573	0.29076	0.53181
Within R^2	0.01984	0.02307	0.08663	0.01925

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 17. Heterogeneous DiD Regression Results (Airport Trips For Yellow Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	0.0503	0.0518	0.2711***	0.0535
	(0.0388)	(0.0388)	(0.1047)	(0.0393)
Post2019	0.3330***	0.3396***	0.3474***	0.3414***
	(0.0265)	(0.0262)	(0.0740)	(0.0264)
Congestion × Post2019	0.3178***	0.3184***	0.3203***	0.3180***
	(0.0305)	(0.0303)	(0.0777)	(0.0303)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	3,493,341	3,493,341	3,493,341	3,493,341
R^2	0.01857	0.01818	0.01024	0.01908
Within R^2	0.00461	0.00449	0.00874	0.00458

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 18. Heterogeneous DiD Regression Results (Airport Trips For Green Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	0.6103	0.7219	1.246***	0.6390
	(0.5050)	(0.5010)	(0.3243)	(0.5021)
Post2019	0.3779***	0.3677***	0.3705***	0.3576***
	(0.1095)	(0.1135)	(0.1105)	(0.1143)
Congestion × Post2019	1.786***	1.579***	0.8792	1.803***
	(0.5406)	(0.5331)	(0.9652)	(0.5271)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	17,370	17,370	17,370	17,370
R^2	0.21629	0.21354	0.06704	0.21737
Within R^2	0.00241	0.00225	0.00391	0.00231

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 19. Heterogeneous DiD Regression Results (Holiday Trips For Yellow Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	1.601***	1.628***	1.080***	1.627***
	(0.1996)	(0.2032)	(0.2127)	(0.2025)
Post2019	-0.0689*	-0.0944**	-0.1561	-0.0986**
	(0.0394)	(0.0393)	(0.1472)	(0.0394)
Congestion × Post2019	2.766***	2.773***	2.904***	2.770***
	(0.0505)	(0.0505)	(0.1503)	(0.0505)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	5,939,313	5,939,313	5,939,313	5,939,313
R^2	0.13016	0.13290	0.08770	0.13363
Within R^2	0.04920	0.04442	0.04860	0.04195

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 20. Heterogeneous DiD Regression Results (Holiday Trips For Green Taxi)

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	1.612***	1.818***	4.638***	1.782***
	(0.2496)	(0.2705)	(0.1447)	(0.2673)
Post2019	1.009***	1.108***	2.348***	1.108***
	(0.0413)	(0.0439)	(0.0772)	(0.0439)
Congestion × Post2019	1.614***	1.662***	1.438***	1.638***
	(0.0925)	(0.0946)	(0.1045)	(0.0950)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	384,428	384,428	384,428	384,428
R^2	0.42348	0.42256	0.19788	0.42671
Within R^2	0.01296	0.01534	0.08662	0.01396

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 21. Robustness Check: Baseline Regression with Redefined Tip Ratio – Yellow Taxi

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	-3.331	-3.059	-4.221**	-3.163
	(2.517)	(2.554)	(1.649)	(2.560)
Post2019	0.750	0.712	1.611	0.752
	(2.273)	(2.241)	(2.195)	(2.242)
Congestion × Post2019	3.448	3.588	2.706	3.553
	(2.286)	(2.262)	(2.210)	(2.262)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	130,249,148	130,249,148	130,249,148	130,249,148
R^2	0.00366	0.00366	3.07×10^{-5}	0.00367
Within R^2	1.16×10^{-5}	1.15×10^{-5}	2.33×10^{-5}	1.18×10^{-5}

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 22. Robustness Check: Baseline Regression with Redefined Tip Ratio – Green Taxi

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	3.249***	3.629***	5.862***	3.470***
	(0.2610)	(0.2764)	(0.1909)	(0.2576)
Post2019	0.4109***	0.4828***	0.5786***	0.4986***
	(0.0566)	(0.0583)	(0.0800)	(0.0565)
Congestion × Post2019	3.499***	3.615***	4.339***	3.530***
	(0.1582)	(0.1620)	(0.1444)	(0.1617)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	7,647,451	7,647,451	7,647,451	7,647,451
R^2	0.21605	0.21377	0.12103	0.22033
Within R^2	0.00570	0.00765	0.03804	0.00642

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 23. Robustness Check: Baseline Regression with Redefined Congestion Zone – Yellow Taxi

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	2.512***	2.570***	0.979***	2.563***
	(0.3377)	(0.3487)	(0.2446)	(0.3466)
Post2019	-0.202**	-0.192**	-1.108***	-0.191**
	(0.0822)	(0.0854)	(0.1332)	(0.0844)
Congestion × Post2019	2.808***	2.822***	3.766***	2.819***
	(0.0828)	(0.0856)	(0.1363)	(0.0847)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	130,249,148	130,249,148	130,249,148	130,249,148
R^2	0.11990	0.12212	0.08826	0.12290
Within R^2	0.05437	0.05360	0.06008	0.05360

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 24. Robustness Check: Baseline Regression with Redefined Congestion Zone – Green Taxi

Dependent Variable:	Tip Ratio			
Model:	(1)	(2)	(3)	(4)
Variables				
Congestion	2.490***	2.701***	4.630***	2.595***
	(0.2477)	(0.2471)	(0.1383)	(0.2374)
Post2019	0.2864***	0.3408***	0.5138***	0.3504***
	(0.0360)	(0.0363)	(0.0521)	(0.0355)
Congestion × Post2019	2.462***	2.528***	2.886***	2.473***
	(0.0702)	(0.0717)	(0.0701)	(0.0719)
Fixed-effects				
Pair	Yes	Yes		Yes
Day Of Week	Yes		Yes	Yes
Pickup Hour	Yes		Yes	Yes
Month		Yes	Yes	Yes
Distance Bin		Yes	Yes	Yes
Fit statistics				
Observations	7,647,451	7,647,451	7,647,451	7,647,451
R^2	0.40191	0.39739	0.19827	0.40514
Within R^2	0.01251	0.01581	0.08718	0.01358

Note: Clustered (Location Pair) standard errors in parentheses
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.