Impact of Manhattan Congestion Surcharge on Commuter Transportation Choices in New York City

Katie Voorhees[1], Rufei sheng[1], Xiaoning He[1], Soham[1], and Sam Manzi[1]

[1]New York University

July 25, 2019

Abstract

Comprehensive understanding of anticipated impacts of transportation pricing policies in an urban system is crucial for both decision-makers and stakeholders. Estimating these impacts can be challenging due to the complexity of transportation systems like New York City's and the lack of complete ground truth data. This paper aims to provide a data-driven framework for quantitative evaluation of such impacts with the recently introduced Manhattan Congestion Surcharge as the case in point. To do so, we will use open data to develop a predictive model to estimate the impact of pricing changes on the demand for public transportation and For-Hire Vehicles. This paper's results include a thorough analysis of economic, social and environmental impacts anticipated as a result of the policy, aimed to enable voters and policymakers to quantitatively evaluate the potential outcomes of congestion pricing.

Introduction

Commuters in New York City have a plethora of options. Subways, buses, ferries, private vehicles, taxis, bike-shares and a growing market of ride-sharing platforms are now being met with share programs for electric scooters and bikes. Despite the bevy of choices, much of New York's growing population finds itself regularly frustrated while traversing the city. Subways are experiencing an increasing amount of delays (Pearce, 2018) due to an aging infrastructure. Driving speeds in Manhattan's Central Business District (south of 60th street) have slowed to an average of 7.2 mph, with speeds in the "Midtown core" 30% slower than the rest of the CBD (DOT, 2018). While public transit is the top over-all choice of NYC commuters, public transit ridership has been declining since 2015 (MTA, 2017), exacerbating financial challenges at the MTA. Department of Transportation (DOT) officials attribute the loss in ridership to consumers increasingly choosing For-Hire Vehicles (FHV), particularly during off-peak hours. The challenges facing NYC's complex transportation ecosystem have motivated this research.

New York lawmakers have responded to these challenges with an initiative unprecedented in the United States - congestion pricing. With aims to relieve traffic and recover some diverted revenue, New York State's Department of Taxation and Finance imposed a congestion surcharge on February 2, 2019, targeting taxis and FHVs(of Taxation & Finance, 2018). The tax adds \$2.75 to FHV trips, \$2.50 to taxi trips and \$.75 to ride-share or pool trips. The tax applies to every trip that begins, ends or passes through Manhattan south of 96th Street. On April 1, 2019, the NY State budget passed, approving a future congestion tax for all vehicles entering Manhattan's CBD below 60th St.(Assembly, 2019). Revenue from the tax is earmarked for MTA capital investments, but this larger scale congestion pricing scheme is not scheduled to be in effect until December 2020 at the earliest. The tax will collect around \$10 from both for-hire and private vehicles and will likely include exemptions for congestion zone residents with lower incomes and drivers with disabilities.

This research will use open data to model the dynamics behind transportation mode shift in New York City. We will use this data-driven model to explore the impacts of the initial Feb. 2, 2019 congestion tax and anticipate the mode shift that may be provoked by the December 2020 implementation of larger scale congestion pricing. Below we will discuss the experiences of other world cities that have implemented congestion pricing as well as relevant work on estimating the impact of transportation interventions.

Literature Review

Our project builds upon the previous work done at Center for Urban Science and Progress (CUSP) on the 'Impact of Bike Sharing in New York City' (Sobolevsky, Levitskaya, Chan, Postle, & Kontokosta, 2018) which looks into the balanced baseline scenario based on a transportation choice model to describe projected customer behavior in the absence of the Citi Bike system and provides proof of concept for this research. We also build on the 'Prediction of Mode Shift in New York City' (Capstone, 2018) project which examines the disruption of subway ridership during the morning rush hour due to app-based ride-hailing services(specifically Uber). Tong has observed how the built environment, individual characteristics, and trip-based variables play a significant role in mode choice decisions(Tong, 2015).

It is notoriously difficult to estimate the impact of congestion pricing on traffic outcomes in cities. Congestion policies are often well publicized and discussed prior to implementation, affording users the opportunity to adjust their behavior ahead of time–for instance, altering schedules to avoid the surcharge, or altering routes to bypass the congestion zones altogether. Congestion pricing policies are often accompanied by an expansion of public transit service in or near the pricing zones, which further obfuscates their impact (Gibson & Carnovale, 2015-2016). However, Gibson et al. exploit a natural experiment in the city of Milan to estimate the price elasticity of vehicular volume under such a congestion surcharge policy. In 2012, a municipal court unexpectedly suspended Milan's surcharge pricing in "Area C" before reinstating it several months later. The sudden nature of the ruling precluded the typical measures (increased public transport, altered parking fees, etc.) that accompany changes in congestion pricing. Thus, Milan's unanticipated injunction provides a unique opportunity to estimate the effect of congestion pricing independent of other factors.

Gibson et al. find that congestion pricing in Milan's "Area C" reduced vehicle entries into the area by 14.5 percent. In their examination of Stockholm's 2006 congestion charge trial, Jonas Eliasson et al. (Eliasson, Hultkrantz, Nerhagen, & Rosqvist, 2009) find consistent estimates of decreases of 18-22 percent in surcharge moderated traffic zones (dependent on time of day). Gibson et al. also observed a reduction in air pollution of 6 to 7 percent, with benefits expanding beyond the targeted zone, and a net economic benefit of ~3 billion USD annually. According to Dr. Paolo Beria of Politecnico di Milano, the policy generated 13 million Euros in revenue one year after its implementation(Beria, 2016). They estimate the price elasticity of vehicular entries to be a .3 percent reduction per 1 percent increase in congestion surcharge. In *Downtown Congestion Pricing in Practice,* a study of congestion surcharge practices in Singapore, London, Stockholm, Milan and Gothenberg, Lehe notes a "zero price effect", wherein the majority of the reduction in congestion priced traffic zones can be attributed to the imposition of a non-zero charge.(Lehe, 2019) They note a marked attenuation in traffic abatement as congestion charge increases. Nonetheless, these analyses provides a compelling basis to consider congestion pricing in urban high traffic zones as a legitimate policy initiative.

One of our primary aims is to evaluate the economic impact of transportation mode shift under various pricing scenarios. A highly relevant conclusion of Gibson et al. is that areas with low access to public transportation are far more sensitive to congestion pricing than are areas with high availability of public transit. Armed with the knowledge that congestion pricing may place a heavier burden on residents who live in transit deserts, policymakers might be better equipped to evaluate the social equity of various pricing scenarios.

Literature review pertaining to our model can be found in the Appendix.

Data

The key elements of our model required us to estimate the time and cost associated with trips between each taxi zone pair (O-D pair) for each of the six transportation modes (taxi, FHV, shared FHV, public transportation, walking, private vehicle). Additionally, in order to evaluate the utility of each transportation mode, we needed to approximate the rider's wages. Our major data sources used were

To determine the time and cost of taxi and For-Hire Vehicle trips between each O-D pair we aggregated trip level data provided as open data from the Taxi and Limousine Commission (TLC). We focused on the morning commute hours of 6 am to 10 am and took the average duration and cost of all trips for the year in that O-D pair during that time. Shared for hire vehicles presented an additional challenge as the TLC indicates which trips are shared, but does not include price information for those trips. To determine the cost per rider of shared FHV trips we aggregated data from the Uber API, pulled live during the commute hours on several work days, taking the average for each O-D pair.

We assumed a constant \$2.75 price for public transportation trips. Walking trips were considered free of cost. The time durations for both public transportation and walking trips were estimated from data called from the HERE Maps API. Like the Uber API, the HERE Maps API provides a live estimate of trip time between durations. To try and limit the impact of any special circumstances that would impact these estimates, we retrieved the data on several occasions and took an average.

The trip time for private vehicles was assumed to be the same as the taxi duration for O-D pairs with that information available (most). If taxi trip duration was not available we supplemented it with duration estimates from the HERE Map API. The cost of private vehicle trips was calculated by estimating the cost of gas, vehicle wear and tear, and parking. Gas and wear and tear was estimated to cost \$0.61 per mile, a figure drawn from transportation research. Parking was estimated to be \$5 outside of the congestion zone and \$15 within the zone (a conservative estimate). While parking cost was approximated, we thought it a valuable inclusion as parking costs are often prohibitive in New York City and a reason many people choose transportation alternatives.

Data from two Census products - the American Community Survey and LEHD Origin-Destination Employment Statistics (LODES) - was used to determine the transportation demand between O-D pairs (LODES) and the wage distribution of each taxi zone (ACS). Initial exploration of the LODES data supported our choice to focus on the commute hours of 6 am to 10 am. We found that the LODES demand was most correlated with the actual TLC data for those hours (see chart in Appendix) , and this correlation allows us to assume that the trip origin is the rider's home taxi zone, enabling us to infer the rider's wages from ACS data on that zone. ACS data on transportation preferences was used to train our model. One limitation of this was that For-Hire vehicle preferences were not segmented into taxi, app-hailed FHV and shared FHV - so we inferred those proportions from the recorded TLC data, which does differentiate.

We have aggregated all data sources to the TLC taxi zone level and the final version of the data which is used in the model includes pickup and drop-off locations, commute duration, price, and the wage distribution for that origin-destination pair.

A more detailed explanation of the data sources and processing can be found in the Appendix along with insights from our initial data exploration.

Methodology

In order to quantify the impact of the Manhattan Congestion Pricing policy, we have compared the simulated ridership under the new pricing scenario against the simulated baseline scenario. For that purpose, we have first used the LEHD/LODES as a proxy for urban mobility, then trained a model based on choices reported in ACS and actual proportions of taxi, FHV and shared FHV observed in the data, and finally compared the simulated ridership to the prior observed preferences to assess the predicted modal shifts.

Specifically, we have simulated the outgoing commute flow in each taxi zone. The simulation studies trips from 6:00 am to 10:00 am, as this period shows high correlation between demand and actual trip amount. Outgoing commute flow is distributed by destination and wages (which influence the utility trade-off between time and cost of different transportation alternatives). The transportation choice proportions (taxi, FHV, shared FHV, public transportation, and walking) for each origin-destination pair will be predicted using the nested multinomial logit model (NMNL). Our transportation choice model is a two-level nesting structure. Six transportation alternatives (numbered as $j = 1, 2, 3, 4, 5, 6$) are partitioned into 4 nests N_1 (taxi, FHV, shared FHV), N_2 (Public Transit), N_3 (walking) and N_4 (private vehicle) . The utility score for alternative j is

$$U_j = -\lambda(T_j W + P_j) + \varepsilon_j \tag{1}$$

where T_j and P_j refer to the time taken and the cost for choosing alternative j between the pair of taxi zones in consideration, W is the hourly wage of the commuter which we sampled from the wage distribution of the origin taxi zone. Here, the parameter λ determines the shift between each alternative. As opposed to the classical use of utility functions where we are trying to increase its value, we want the alternative which produces the lowest utility score. That is why we have given a negative co-efficient to the deterministic part of the utility $V_j = -\lambda(T_j W + P_j)$. The deterministic part V_j has been used to calculate the probability of each outcome $P(y = j)$; where $y \in 1, 2, 3, 4, 5, 6$ indicates the chosen mode. Within a nest k, the degree of dissimilarity between the transportation alternatives is indicated by the dissimilarity parameter τ_k. The marginal probability of the outcome j is

$$P(y = j) = \frac{e^{\frac{1}{\tau_k} V_j}}{e^{IV_k}} \cdot \frac{e^{\tau_k V_j}}{\sum_m e^{\tau_m IV_m}} \tag{2}$$

with the inclusive value IV_k (which signifies how inclusive each nest is based on its dissimilarity parameters Tau) defined as

$$IV_k = \ln \sum_{l \in N_k} e^{\frac{1}{\tau_k} V_l} \tag{3}$$

The probability for each origin-destination pair for each transportation mode has then be multiplied by the commute population in that OD pair, and has been aggregated by origin. We have used the American Community Survey (ACS) data as the ground-truth on the relative distribution of population's choices for each mode. We tune the parameters by comparing the model results with ground truth. For this comparision, we initially used 10 only randomly chosen taxi zones; and then, in a more enhanced version, used the taxi zones which cover 60% of the population. We applied grid search to these selected taxi zones. The loss functions that we used were root of mean square error(RMSE), normalized RMSE, weighting cumulative loss and RMSE based on total population for each mode. The reason for using more than one loss function was that no single one was able to give out good parameters by itself. Finally, we picked the best parameters from 48 combinations of our parameters(Tau=0.05 and Lambda=1.5). A limitation of this parameter tuning is that we are tuning parameters based on the results of only 60% of the population as running the simulation for the whole dataset takes more than an hour per iteration. Finally, we have run the model with these parameters for three scenarios – normal price without congestion surcharge, increase in price by \$2.75 (current scenario), and increase in price by \$10 (surcharge proposed to be implemented in 2020) and compared the outcomes of these. We also added a level of uncertainty in our results by using 5 of the best sets of parameters and reporting their mean and standard deviation.

Model equations not included here can be found in the Appendix.

Model uncertainty and data scaling

As mentioned in the modeling section, in order to see how accurate our results were, we also decided to add a level of uncertainty to the results of our model. So, instead of just reporting the results of the parameters with the lowest RMSE, we ran all 3 of our scenarios for 5 sets of parameters which had the lowest values of RMSE and then, we weighted the results of each set of parameters proportional to a negation of their RMSE and used the mean and standard deviation of the resulting distribution in all the impacts we analyzed.

Additionally, we scaled the resulting mean of scenario-1 so that, it would become the same as the ground truth value. The advantage of doing this is that our results become more equivalent to the real-world scenario which is what the ACS (ground truth) represents. And then, we scaled the means for scenarios 2 and 3 as well as the standard deviations for all the scenarios by the same ratio that transformed the mean of scenario-1 to the ground truth so that the relativity of the model results could be maintained.

Table-1 shows the relative values of standard deviation for each mode and scenario relative to the mean value so that we can get a better idea of what sort of variation to expect from the model results.

Results

The ultimate goal of this research is to apply our transportation mode shift model in order to quantitatively evaluate the anticipated impacts of Manhattan Congestion Pricing. To evaluate this impact, we applied our model to three pricing scenarios, each reflecting a Congestion Pricing policy scenario:

1. Status quo (no surcharge added to price)

2. Existing Congestion Pricing surcharge ($0.75 - $2.75 added to nest 1 trips passing through the Congestion Zone, as trip data was collected before the existing policy went into effect)

3. Proposed Congestion Pricing surcharge ($10 added to nest 1 trips and private vehicles passing through the Congestion Zone)

Throughout the analysis of our results, we will refer to "Scenario 1", "Scenario 2", and "Scenario 3" to reference the policy scenarios outlined above. The time frame of our result is daily during morning commute hours (6 am -10 am).

We analyzed the model outputs to determine the anticipated effect of each policy on the NYC transportation system as a whole (i.e. a total shift in public transportation ridership, walking, taxi/FHV, and private vehicles ridership) as well as the anticipated effect on economic, social and environmental factors.

Mode shift under each scenario

The two tables below show the shift in NYC wide transportation choices projected for each policy scenario. We took the weighted average of 5 sets of our best models as the final results and calculated the weighted standard deviates as uncertainties of each value. The results are scaled based on the "ground truth" - the commuting transportation mode choices reported in the American Community Survey(ACS) to ensure they matched with the realities. Our model predicts a reduction in Taxi, (non-shared) FHV, and private vehicle trips under both Congestion Pricing Scenarios. We predicted an overall 0.16% drop (about 4,600 trips) in Taxi and (non-shared) FHV trips during the daily morning commute hours under the $2.75 tax, and an overall 0.25% drop (about 65,00 trips) under the $10 tax. The private vehicle trips decrease 0.16% (about 1,500 trips) under the $2.75 tax and 2.89% (about 62,000 trips) under $10 tax. The model predicts an increase in Shared FHV trips, Public Transportation trips, and Walking trips in both scenarios.

Anticipated impact on MTA, taxi, FHV revenues, and Tax revenues

Our major results are reported in Figure (1). This bar chart on the left shows the change in revenues with uncertainties for Public Transportation(MTA), Taxi, FHV, and Shared-FHV under each price scenario. Corresponding to the mode shift, there are predicted a reduction in Taxi and (non-shared) FHV revenues under both Congestion Pricing Scenarios, and an increase in Shared- FHV and MTA revenues. The table on the right displays the actual amount of change in dollars between scenarios with the corresponding percentage. Taxi revenue has the biggest percentage drop (up to 46% decrease), and MTA has the greatest growth in number (about $72,000 and $551,000). Non-shared FHV has a slight decrease in revenues under each price scenario, however, the increase in shared FHV (up to 65% increase) can easily cover that loses and creates extra profits for the total FHV revenue (the overall FHV revenue increases $14,771 from status quo to $2.75 tax and $33,818 from $2.75 to $10 tax).

Table (4) shows the Tax Revenue from the Congestion Surcharge under each scenario. We compare our predicted tax revenue with a "zero scenario" revenue- the expected revenue if the surcharge were imposed and no commuters change their mode choice behaviors. The results show that both of the predicted revenues after the mode shift in scenario 2 and 3 are about 50% lower than the zero scenario revenues. We believe that this shows the advantage of our methodology, as the use of a mode shift model provides a more realistic prediction of future revenues, as it accounts for behavior changes resulting from the tax. Policy makers using the zero scenario might vastly over-estimate surcharge tax revenues.

All of the 37 origin taxi zones that the model predicts will experience the most mode shift under the $10 Congestion Tax (predicted change is more than 28.57%, which is one standard deviation above the mean predicted change) are in Manhattan. As seen in Figure (2), the geographic range of impact is much larger in Scenario 3 ($10 surcharge). Our model did not assume any exemptions for residents of the congestion zones, and our results suggest that decisions around those exemptions may significantly affect the impacts of the policy.

Anticipated daily impact on commuter time and expenses

As seen in Tables (5) and (6), the subway ridership and the commute time increased for both the scenarios but, the change is more significant for the $10 Congestion Tax Scenario. So, we can see that the average commuter will spend not only more time on their commute but will also, most likely, have to commute in more crowded subway cars. Also, an interesting impact seen here is that the commute cost increases slightly in the $2.75 congestion tax scenario in contrast to it reducing in the $10 scenario. This is because the model predicted that most of the taxi and FHV commuters simply switched to either shared FHVs or stuck to their mode of choice and just paid the surcharge instead of shifting to the subway which dramatically cut the cost which makes sense too as people are usually very reluctant to change their transportation mode.

Anticipated environmental impact

The earlier cited work of Gibson, et. al provides a framework for us to quantitatively evaluate the predicted environmental impacts of the surcharge scenarios. They found that for every daily vehicle reduction emissions would be reduced by .00006552 microgram/meter cubed. They then presented a framework for quantifying the economic benefit of this emissions reduction. They cite 1984 US government research that estimated that people were willing to pay $148.70 ($366.59 in 2019) per year per person for every microgram/cubic meter reduction in pollution. If we assume that every 60 miles (during the 6 am to 10 am morning commute window) in driving distance represents one vehicle (conservatively assuming a constant 15 miles per hour), we can estimate the number of vehicles reduced. From this framework we predict a very small reduction of 29 (+-15) cars per commute window under the $2.75 surcharge scenario and a reduction of 9,060 (+- 40) cars during the morning commute under the $10 scenario. This includes total mileage reduction from taxis, FHVs and private vehicles and accounts for the additional miles from the predicted increase in shared FHVs. Under scenario 2 we would approximate a negligible daily reduction of pollutants by .002 (+-.001) micrograms/meters cubed, for a yearly reduction of 0.7 (+- 0.35) attributed to the effect of the $2.75 surcharge on the morning commuter. Under scenario 3 the framework presented by Gibson, et.al would predict a daily reduction of approximately 0.6 (+-.003) micrograms/meters cubed for a 217 (+-1) microgram/meters cubed yearly reduction of harmful pollutants attributed to the morning commute hours. If we multiply that total by the $366.59 per year a person is willing to pay for a reduction in unit of pollutants, we get a yearly value of $79,430 (+-$353) per person impacted. Applied to the approximately 1.3 million people living in Manhattan's congestion zone, the reductions environmental benefits are significant. Notable from Gibson, et. al. was the finding that air quality benefits expanded beyond the congestion zone, suggesting an even larger range of environmental benefit is possible.

Equity evaluation

In order to evaluate any potential equity or accessibility concerns with the existing or proposed congestion tax, we compared our model's predicted mode shift segmented by wage bracket. Figure (3) plots the predicted percentage reduction (right) in vehicle commutes from the baseline Scenario 1 to Scenario 3 - the proposed \$10 surcharge - by income bracket, as well as the original percent of commuters in each bracket who choose taxi/FHV/private vehicle (left). Many vehicle-based commuters make fewer than \$100,000 per year, suggesting potential for a congestion surcharge to weigh heavily on lower and middle income commuters. When plotting predicted mode shift as a result of the surcharge, it becomes clear that of all vehicle commuters, those making under \$25,000 may feel the most impact in terms of mode shift as a percentage of vehicle commuters.

As seen when comparing the two plots in Figure (4), a higher percent of commuters working in the congestion zone is associated with a higher percent of vehicle commuters predicted to change modes. This makes sense as commuters not living or working in the congestion zone will not be affected by the surcharge during their workday commutes.

As seen below in Figure (5), the percent of people working in the congestions zone is associated with a higher median income at the taxi zone level. Additionally, the percent of people working in the congestion zone is associated with a lower percentage of people in that zone reporting private vehicles as their transportation choice, suggesting that many private vehicle commuters may not work in the congestion zone, and may not be impacted by the surcharge on their daily commutes. Referring again to Figure (3) those lower income commuters who do work in the congestion are predicted to shift modes at a higher rate, potentially creating a prohibitively long commute.

To explore accessibility concerns, Figure (6) has been included to show the distribution of residents over the age of 65 or with a disability. While our model estimates mode choice based on a trade off between time and cost, these populations may have additional concerns that might prevent them from switching modes, particularly to public transportation, even if a surcharge made their vehicle-based commute prohibitively expensive. While the final details of the proposed \$10 surcharge are not yet available, most news accounts report that there will be an exemption or discount for populations with accessibility concerns, particularly for those living in the congestion zone.

Limitations

As seen in the results of the model, the uncertainty in nest-1 modes which are taxis and FHV ranges between 20-80%(depending on the scenario and mode), which is very high. This means that the predictions of nest-1 are extremely sensitive to the parameters chosen which means that the parameters need to be very precise and even slight changes to them would result in huge changes in the predictions. it over-predicts the counts for the taxis and FHVs by a huge number as compared to the ground truth data (ACS +LEHD). One reason behind this is that the ACS data is outdated and so, it is unable to give reliable proportions for the taxi and FHV usage during this so-called 'FHV-era'. So, we are doing parameter tuning based on the ground truth while the ground truth itself might not be very representative of the actual situation and so, the predicted results today might differ by a lot from the ACS+LEHD. Another reason behind this huge gap could be that the Utility function does not reflect well enough how a person makes a transportation choice. The utility function would work very well in an ideal world where everyone worked out the economics of their commute on a daily basis but, the reality of transportation choices is influenced by habits, comfort preferences, and other human factors. Another limitation is the narrow scope of our study of morning commuters. This population does not represent a complete picture of the transportation system and may have particular preferences or characteristics that would mean that a model fit to commuters wouldn't be generalizable to the rest of travelers.

Conclusions

Broadly, our results indicate that congestion surcharge policy in Manhattan will have the intended effect - to decrease vehicle traffic in the congestion zone and collect surcharge fees which can be used to fund public transportation repairs. Due to the level of uncertainty in our nest 1 data - Taxis, FHV, and shared FHV - and the relatively small change predicted by our model, it is difficult to say conclusively whether we believe the existing \$2.75 surcharge will succeed in reducing traffic. Our results do indicate that the proposed \$10 surcharge is likely to have a significant impact on the effected modes (taxi, FHV, and private vehicles), shifting ridership away from these modes to public transportation. Notably, our model predicts an increase in shared FHVs, which are subject to the surcharge, but the cost is shared between riders. This increase in shared FHV makes up any lost revenue from other FHVs.

While the specifications of the upcoming surcharge implementation are not finalized (or at least not available to the public), and will likely change some of the projected impacts, our results can be informative to voters and policy makers. The application here of a NMLM mode shift model allows us to provide a more realistic picture of anticipated tax revenues from the surcharge. Our tax revenue projections are about 50% of what someone would predict if assuming that no behavior change would result from the congestion surcharges, and our results indicate a potential for increased crowding on subways.

That said, further work remains to develop a comprehensive and accurate picture of mode shift. We focused our study on commuters because it allowed us to infer demographic and transportation demand information, but the morning commute takes up a small part of New York City's complex transportation system. The collection of more accurate ground truth data, perhaps using cell phone location data, could improve the outcomes of this model. Finally, while we hope that this study can be a proof of concept for other city's considering similar policies, it should be noted that New York City's transportation system is unique in many ways, and makes a switch to public transportation more practical than many other cities.

Figures:

Mode	Standard deviation for Scenario1	Standard deviation for Scenario2	Standard deviation for Scenario3
1- Taxi	0.25	0.29	0.16
2- FHV	0.35	0.31	0.3
3 - Shared FHV	0.45	0.54	0.66
4 - Subway	0.01	0.01	0.0
5 - Walking	0.01	0.01	0.0
6 - Private Vehicles	0.01	0.01	0.0

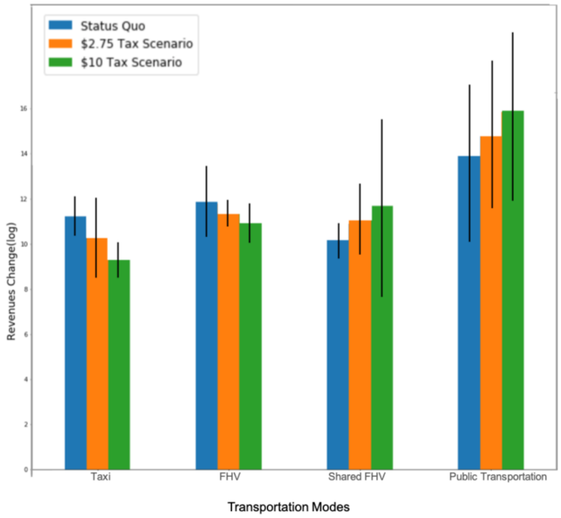
Table 1: This table shows what percentage of the mean values the standard deviations are for each mode. As you can see, modes 1, 2 and 3 have very high percentages for the standard deviation while the values are <1% for the other modes.

	Taxi	FHV	Shared FHV	Public Transportation	Walking	Private Vehicles
Status Quo Model	9721	14753	5745	1756041	307192	786565
$2.75 Tax Model	5755 (±157)	14121 (±435)	8083 (±602)	1778145 (±2853)	309132 (±99)	788142 (±433)
$10 Tax Model	3899 (±256)	14067 (±499)	11442 (±2075)	1900522 (±6126)	310972 (±188)	724123 (±758)

Table 2: This table shows a distribution view of the scaled results of our model simulations. Numbers represent the number of trips for each mode predicted under each scenario during the daily morning commute hours. The level of uncertainties for scenario 2 and 3 is stated inside the pretenses after each value. Scenario 1 does not have uncertainty because scenario 1 results from all the models are scaled based on the ACS data.

	Taxi	FHV	Shared FHV	Public Transportation	Walking	Private Vehicles
Status Quo Model	0.0	0.01	0.0	0.61	0.11	0.27
$2.75 Tax Model	0.2% (± 0%)	0.49% (± 0.01%)	0.28% (± 0.02%)	61.24% (± 0.02%)	10.65% (± 0.01%)	27.15% (± 0.01%)
$10 Tax Model	0.13% (± 0.01%)	0.47% (± 0.02%)	0.39% (± 0.06%)	64.1% (± 0.03%)	10.49% (± 0.02%)	24.42% (± 0.04%)

Table 3: This table shows the proportion of total NYC commute trips for each mode predicted under each scenario. The level of uncertainties for scenario 2 and 3 is stated inside the pretenses after each value. Scenario 1 does not have uncertainty because scenatio 1 results from all the models are scaled based on the ACS data.



Change in Revenues	From Status Quo to $2.75 Tax	From $2.75 Tax to $10 Tax
Taxi	**- $ 33,480** (± $594) [- 44%~46%]	**- $ 13,759** (± $2,443) [- 32%~ 41%]
FHV	**- $ 7,864** (± $3,558) [- 1%~6%]	**- $669** (± $893) [-1% ~ 0%]
FHV - Shared	**+ $ 22,636** (± $3,866) [+42% ~54%]	**+ $ 34,482** (± $13,195) [+35%~65%]
MTA	**+ $ 72,566** (±$11,250) [+0.8%~1.1%]	**+ $ 551,188** (±$10,703) [+7.1%~7.3%]

Figure 1: This figure shows the distribution of the revenues for the four transportation modes under different price scenarios, along with the actual amount of change with uncertainties and percentage intervals displayed in the table. A logarithmic scale has been applied to the bars due to the large difference between public transportation revenue and other revenues.

Tax Revenue	Zero Scenario Revenue	Revenue After Predicted Mode Shift
$2.75 Tax Model	$17660 (± $2096)	$9160 (± $1484)
$10 Tax Model	$1235351 (± $762)	$573626 (± $6098)

Table 4: This table displays the baseline Tax Revenue and predicted Tax Revenue each price scenario. The level of uncertainties is stated inside the pretenses after each value.

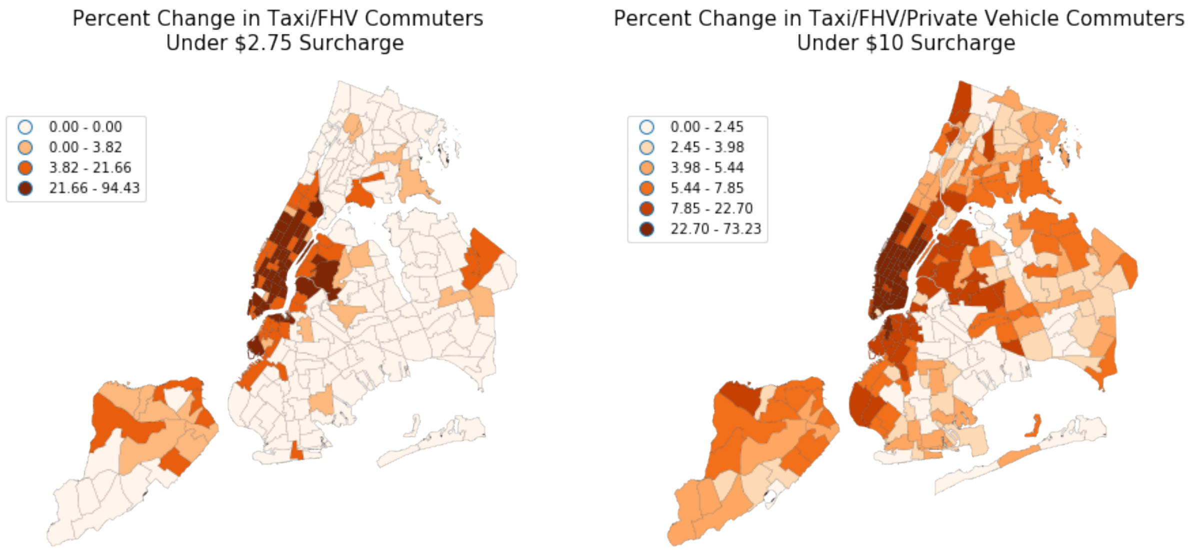


Figure 2: Origin taxi zones on the left are shaded by the predicted percent decrease in total taxi and FHV ridership under the $2.75 Congestion Tax scenario. Origin taxi zones on the right are shaded by the predicted percent decrease in total taxi, FHV, and private vehicle ridership under the $10 Congestion Tax scenario. Manhattan taxi zones in or adjacent to the congestion zone are predicted to experience the largest shift.

Scenarios	Subway Ridership	Average Commute Time(minutes)	Average Commute Cost ($)
Status Quo	1756041 +- 6.7eˆ(-9)	80.6 +- 0.06	8.47 +- 0.02
2.75$ Congestion Tax (Present. Scenario)	1778146 +- 3383	80.49 +- 0.02	8.43 +- 0.07
10$ Congestion Tax (Proposed policy)	1900523 +- 7377	80.95 +- 0.04	8.19 +- 0.01

Table 5: This table shows the subway ridership and the impact on average commute time and cost under the 2 congestion surcharge scenarios. These are derived from the mean values of the distribution created by running 5 sets of parameters with percentage variance as shown in Table 1. We can see an increase in the ridership and commute time but, the cost remains somewhat similar.

Impact on Commute Statistics	Increase in Subway Ridership (%)	Increase in Average Commute Time (%)	Change in Average Commute Cost (%)
Status Quo to 2.75$ Congestion tax	(1.26 +- 0.19)%	(0.67 +- 0.1)%	(0.32 +- 0.18)%
Status Quo to 10$ Congestion tax	(8.23 +- 0.42)%	(3.4 +- 0.22)%	(-0.45 +- 0.44)%
2.75$ to 10$ Congestion tax	(6.88 +- 0.21)%	(2.71 +- 0.13)%	(-0.78 +- 0.29)%

Table 6: This table shows the percentage changes in subway ridership average commute time and cost under the 2 congestion surcharge scenarios. These are derived from the mean values of the distribution created by running 5 sets of parameters with percentage variance as shown in Table 1. We can see a noticeable increase in the ridership and commute time but, the change in the cost is relatively insignificant.

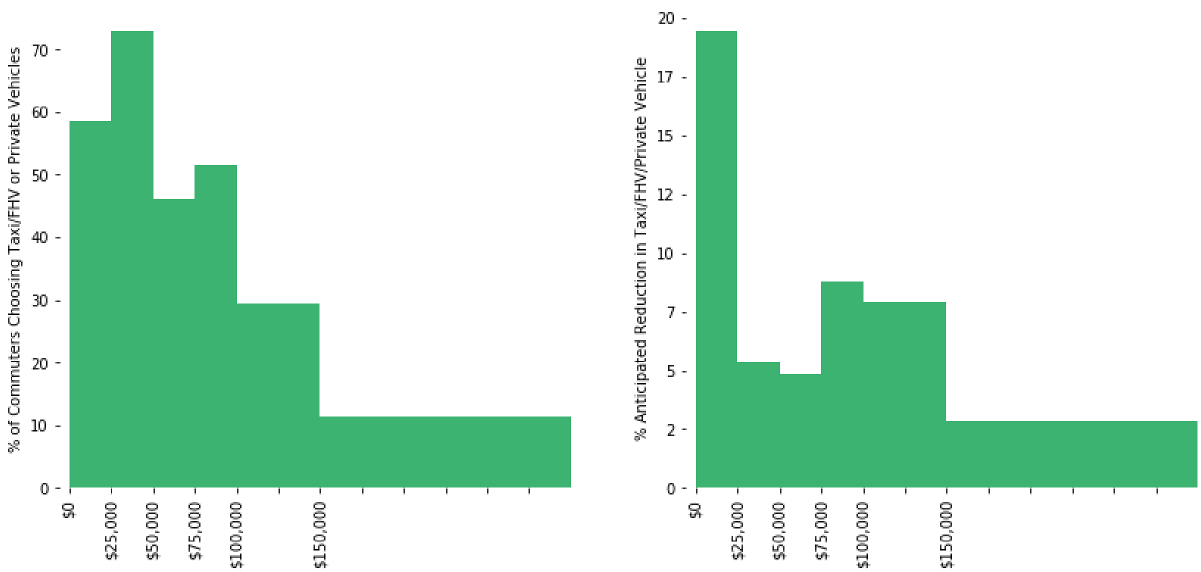


Figure 3: The plot on the left show the percentage of commuters in each income bracket that report using taxi, FHV, shared FHV or private vehicles to commute to work. The plot on the right shows the expected reduction of Taxi, FHV, shared FHV and private vehicles predicted under Scenario 3 - $10 congestion surcharge - by income bracket, as a percent of Scenario 1 vehicle ridership. Amounts represented are the weighted average of the distribution from our five sets of parameters. ACS income brackets are not evenly spaced, so the numbers in each bracket were either summed or divided in order to create a perceptually uniform plot, with each bar representing an income range of $25,000.

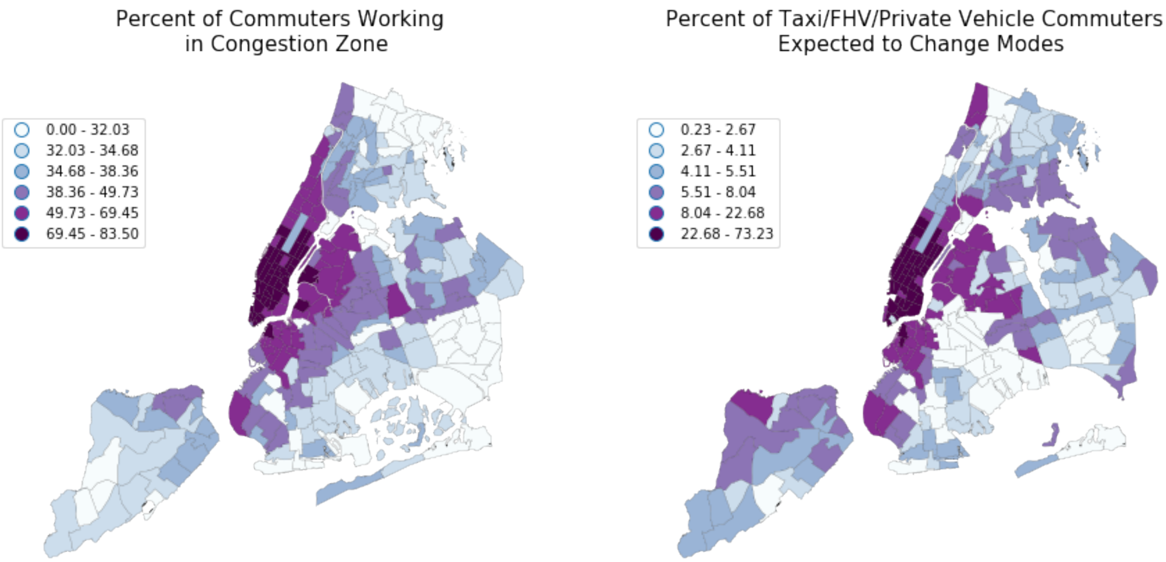


Figure 4: The figure on the left shows the percent of taxi zone residents who work in the congestion zone (shaded by home taxi zone). The figure on the right shows the percent of all taxi, FHV, shared FHV and private vehicle commuters expected to shift modes due to the $10 surcharge. Both figures reference the "Scenario 3" congestion surcharge of $10. The congestion zone referenced is the corresponding zone, Manhattan below 60th st.. Amounts represented are the weighted average of the distribution from our five sets of parameters.

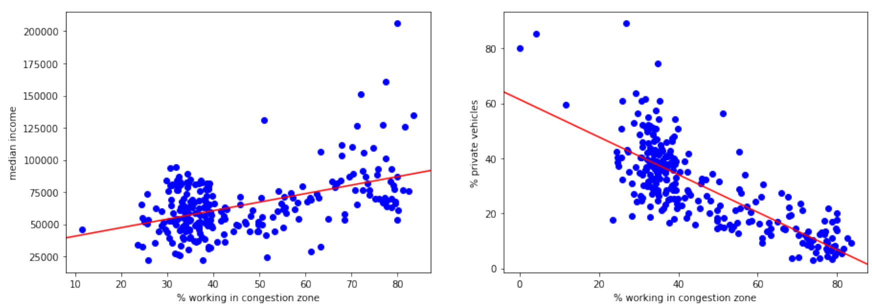


Figure 5: The plot on the left shows the positive correlation between percent of commuters working in the congestion zone and that home zone's median wage. The plot on the right shows the negative correlation between the percent of commuters working in the congestion zone and the percent of commuters choosing private vehicles for transportation to work. Amounts represented are the weighted average of the distribution from our five sets of parameters.

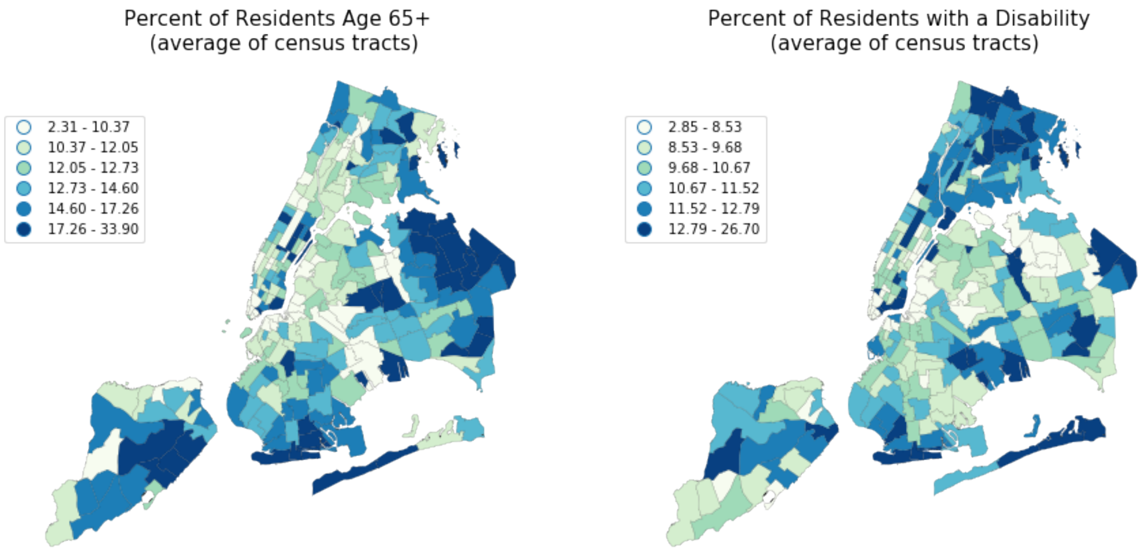


Figure 6: The map on the left is shaded according to the percent of residents in that zone age 65 or over, calculated as an average of all the census tracts in that zone. The map on the right shows the percent of residents with a disability, calculated as the average of all census tracts in that zone.

Appendix:Team Collaboration Statement

Team members worked collaboratively on every aspect of the project. In order to improve the collaboration efficiency and effectiveness, each domain is assigned to several people as "leads" to monitor the progress. Specifically, Xiaoning He and Sam Manzi are responsible for data gathering and cleaning; Rufei Sheng and Soham Mody are responsible for modeling and analysis; Katharine Voorhees is responsible for literature review and report writing. After getting the initial model results, Xiaoning, Soham and Katharine worked extensively on improving model performance and interpreting results while Rufei was in charge of making the project website.

Additional Literature Review (model)

In order to see if there was a mode shift and to assess the impact of the policy, we would need to see if the choices people made for commuting would change with the new pricing or not. So, our model has to simulate the transportation choices(Ramming & Scott, 2002) that commuters make based on factors like their wages, the cost of that transportation mode and so on. The discrete choice model has been proven to be an effective method in the past to do transportation choice modeling(Train, 1977). In economics, discrete choice models, or qualitative choice models, describe, explain, and predict choices between two or more discrete alternatives, such as entering or not entering the labor market or choosing between modes of transport. To work with a discrete choice model, there should be a finite set of alternatives which are mutually exclusive and collectively exhaustive. So, considering the modes we wanted to focus on and the available data, we decided to keep 6 modes: Taxis, for-hire vehicles(FHV), shared FHVs, public transportation, walking, and private vehicles. While this doesn't capture the entirety of New York City's complex transportation system, these modes do represent approximately 95% of daily commuters, accord to the American Community

Survey.

We considered several models for our purpose of modeling transportation choices (Yu & Sun, 2012). There are four typical discrete choice models used in the transportation research we reviewed: Multinomial logit (MNL) model, Nested logit (NL) model, Generalized Extreme Value (GEV) Model and Mixed logit model. Since the choices among taxi, FHVs and shared FHVs are highly correlated with each other, we cannot use (Heiss, 2002) a simple multinomial logit model where all the modes are assumed to be uncorrelated. Also, using a mixed logit model gives too much flexibility as it allows all sorts of correlations but in reality, our primary concern was that the model account for correlation between the taxis and FHVs. In the nested multinomial logit model, the modes in different nests are assumed to be uncorrelated but inside the nest correlation is permissible, and so provides the best fit for our understanding of the NYC transportation system.

Data:

American Community Survey

American Community Survey (ACS) data was used to reflect reported choices of transportation modes by commuters serving as ground truth for fitting the model. Census tract level 5-year estimate data was pulled through the Census API in order to generate probabilities of a commuter within each taxi zone of having wages within each Census income bracket. Because the Census provides bucketed rather than continuous income information, the middle of the bracket range was attached to all individuals in that bracket. Commute information from the ACS was used to estimate the percentage of people in each taxi zone that regularly choose each form of transportation for trips to work. Respondents were asked to report which form of transportation they used "most days" for commuting to work. Collectively the ACS data allows us to estimate the probability of any given resident of each origin zone choosing each distinct mode of transportation, as well as predicting that commuter's income (based on the income distribution of the zone).

	taxi_zone	P(mode1)	P(mode2)	P(mode3)	P(mode4)	P(mode5)
0	3	177.762595	73.068204	1.150001	16668.822855	2001.196346
1	4	201.297419	120.885755	61.223127	13318.123341	6279.470358
2	5	49.601278	7.992997	0.306749	8847.276451	142.822526
3	6	164.390442	40.427858	2.346380	22929.859149	2485.976170
4	7	616.150103	162.371679	110.267353	138012.557541	11998.653324

Figure 7: American Community Survey (ACS) as ground-truth, indicating the population for each transportation model based on each origin taxi zone

Trip Data

Taxi

New York City's Taxi and Limousine Commission provides free access to their database of taxi trip data with ride-level granularity. A typical month of data consists of 10 to 15 million rides. For analysis, we have aggregated at the level of origin-destination, hour of day and day of week; we consider mean passenger count, fare amount, tip amount, trip duration, and total ride volume and passenger volume. These data give a sense of the high volume traffic areas in the city, as well as the distribution of trips by time of day. They are crucial to estimate current modal distribution and, when used in conjunction with demographic ACS data, to predict mode shift under various pricing scenarios and within varying demographics.

Preliminary analysis of taxi ride volume in January 2017 shows that 57 taxi zones account for half of all trips (~4.5 million) (Figure 8). Furthermore, 52 of these taxi zones are in Manhattan, 45 of which are are subject to congestion pricing (Figure 9). Thus, yellow cab drivers and yellow cab riders are obvious stakeholders when it comes to congestion surcharge policy.

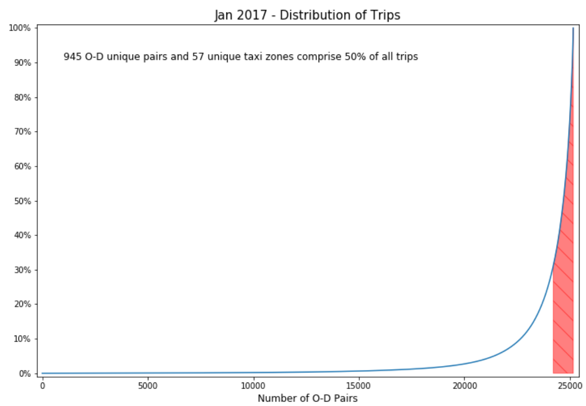


Figure 8: Distribution of taxi trips by origin and destination (taxi zone level). Note that half of the distribution (shaded portion) is comprised of 945 unique O-D pairs and 57 unique taxi zones (see Fig. 2)

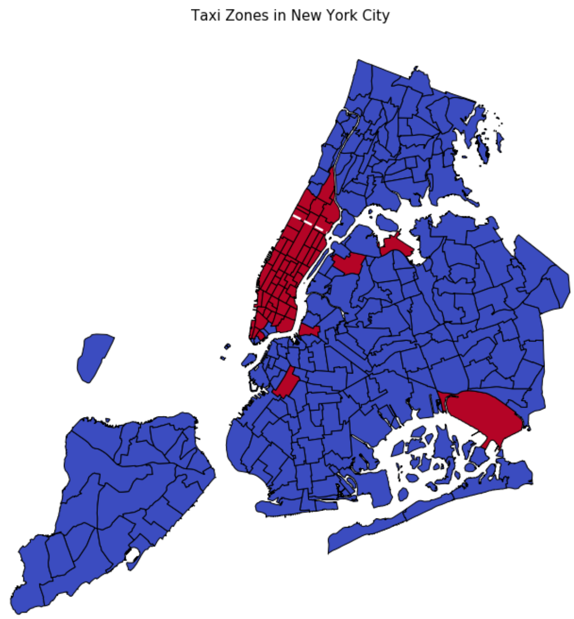


Figure 9: Red taxi zones comprise origins or destinations which constituted 50% of all rides in January of 2017. Zones in Manhattan which lie south of the dashed white line (96th street) are currently subject to congestion pricing.

For-Hire-Vehicles (FHV)

For-Hire-Vehicle trip data are provided by TLC consists of individual trip data for different FHV services (ex. Uber, Lyft, etc.). A typical month of data includes 15 to 20 million rides, with around 20% of shared FHV, and 80% Non-shared FHV. For analysis, we have separated the FHV trips to FHV and shared FHV , and aggregated both data at the level of pickup and Drop-off zone, date and hours from 5 am to 10 am. The aggregated data contains attributes of date, pickup location id, drop-off location id, average trip duration (sec), trip counts, and surcharge flag - SR_Flag(FHV and shared FHV.) .

Uber API

Uber API provides live pricing of Uber rides at the time of the request. Uber has released a Python library called uber-rides which can be used to request the ride information using a server token private to each user. We need the price of shared and non-shared rides in the time interval of our interest which is 8-9 am. But, there is a limit of 2000 requests per hour for a server token and we needed the information for about 70,000 trips (all combinations of the 263 taxi zones). So, we are performing the data curation over several days at the same time using datetime and Timer functions of Python to schedule this process and also looking into other creative methods to approximate this price instead of getting it for each combination. The ideal thing would be to use this price from the actual trips which took place as we are using the time taken for the trip from that data. But since that data is not available, this data is collected at the same time(8-9 am) and it gives a good approximation.

HERE Maps

HERE technology is the company that provides mapping and location data. In order to assess travel time, cost and overall utility of each transportation mode considered in the model given the OD pair, we use HERE REST APIs to gather information such as maps, routing, geocoding, places, positioning, traffic, transit, and weather information. The public transit data can be acquired via specific Public Transit API. Use HTTP GET methods, route information such as the trip time duration, the number of transfer, and the mode for each transfer will be get given departure and arrive location, departure time, and specific mode. The public transit data used in our model is acquired by specifying "mode = subway & bus", while the walking related data using "mode = walking".

Aggregated data

Spatial Join

In order to apply data from the American Community Survey (ACS) and LEHD to this research Census geographies needed to be spatially joined with taxi zones so that we could aggregate the data at the taxi zone level. ACS data was merged with a shapefile of census tract population centroids accessed through NYU's Spatial Data Repository (Repository, 2010), and then spatially joined in GeoPandas to a taxi zone shapefile (Taxi & (TLC), 2019). Similarly, LEHD data was merged with with a shapefile of Census blocks and then spatially joined to the taxi zone shapefile for aggregation.

Modeling dataset

After data processing and aggregation, the final version data for modeling includes pickup and drop-off locations (aggregated on the taxi zone level), commute duration, price, wage distribution. Example is shown in Figure 10.

duration	price	ODpair	2500	7500	12500	17500	22500	30000	
6.508943	16.647073	3-3	11.412271	16.389811	29.504545	12.840609	18.871367	26.936423	30.5
39.695000	64.000000	3-4	0.250819	0.360216	0.648452	0.282211	0.414755	0.592009	0.6
45.216667	61.500000	3-4	0.250819	0.360216	0.648452	0.282211	0.414755	0.592009	0.6
83.000000	5.500000	3-4	0.250819	0.360216	0.648452	0.282211	0.414755	0.592009	0.6
225.933333	0.000000	3-4	0.250819	0.360216	0.648452	0.282211	0.414755	0.592009	0.6
47.880952	43.157143	3-7	1.504915	2.161294	3.890709	1.693267	2.488532	3.552056	4.0
30.521739	47.000000	3-7	1.504915	2.161294	3.890709	1.693267	2.488532	3.552056	4.0
37.159009	45.000000	3-7	1.504915	2.161294	3.890709	1.693267	2.488532	3.552056	4.0

Figure 10: Aggregated Data (Public Transit mode example

Data Exploration

Taxi & LEHD Data Correlation

In order to understand how good of a transportation demand proxy LEHD is , we explored the 2015 LEHD data together with the 2015 taxi data to find the best correlated hours between the LEHD demand the actual taxi ridership. We aggregated the datasets by each pair of pickup and drop-off taxi zone, and by each hour of the day. We calculated the correlations of the hourly trip counts between the total LODES count, and its correlations between the "expected" taxi ridership (total LODES count multiplying by the percentage of census taxi commuters).

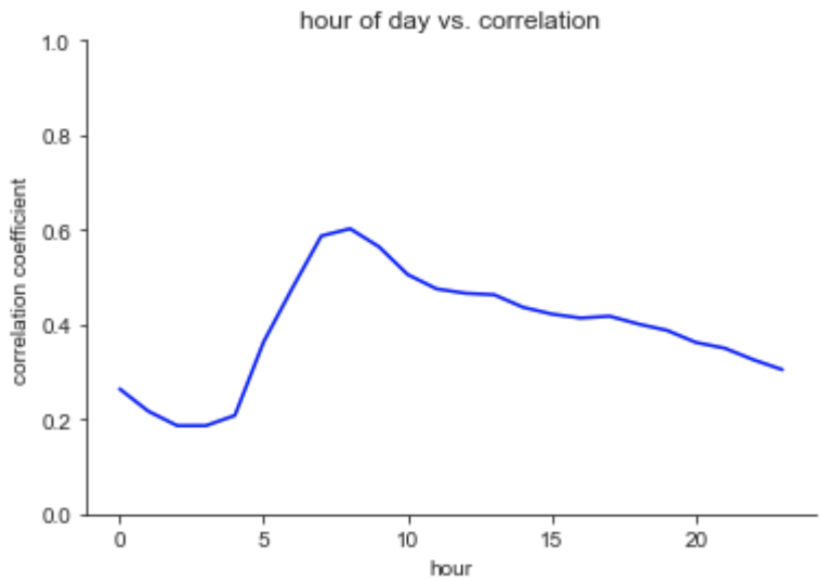


Figure 11: Hourly correlations between actual taxi trip counts for OD pairs and the "expected" taxi ridership for the same pair. "Expected taxi ridership" was calculated as the ratio of people for each OD pair that take a taxi to work on most days (as reported by the ACS) multiplied by the count of commuters for the pair (reported by the LODES data).

The results show the taxi trips during morning hours (5am-10am) is more correlated with both of the expected taxi ridership and the total LODES count compared to other time of the day. A comparison of the two figures reveals that the correlation between actual taxi ridership and the "expected" taxi ridership is much stronger than the correlation between actual ridership and the total LEHD demand. Such results verify our assumption that the morning hours trips are more correlated with the LEHD demands, particularly when paired with ACS data about transportation behaviors. Thus the pickup (origin) taxi zones during the morning hours should be more representative of people's actual residential locations, allowing us to infer information about those travelers based on ACS data (i.e. income distribution). To accurately utilize regional demographic information in our model, we decided to scope our analyzes within the morning hours time frame.

Taxi Data exploration analysis

To better understand the distribution of trips and to select the appropriate proportion of data for our model use, we analyzed the ridership trends of Taxi by aggregating the total passengers, total rides, average fare and average trip duration for each hour of the day. Results show that the morning rush hours (6–10 am) and evening rush hours (5–7pm) usually has more total rides and total passengers in the weekdays (Figure 12). This trend is less obvious during weekends, however, on the weekends there is a noticeable increase in the midnight trips (Figure 13). Based on the mean taxi fare and mean trip duration, we found the trips around 4 pm tend to be longer and more expensive based on the average fare and average trip duration (Figure 14). We also examined the trips distribution for high passenger volume taxi zones, including Times Sq/Theatre District, Penn Station/Madison Square, Lenox Hill West, Lincoln Square, Upper West Side, and Upper East

Side. We found zones that near Central Park (e.g, Lenox Hill, Upper West, and Upper East Site have the highest passenger volume all day from 7 am 7 pm. Zones such as times Sq/Theatre District, and Penn Station have high volume during evening hours.

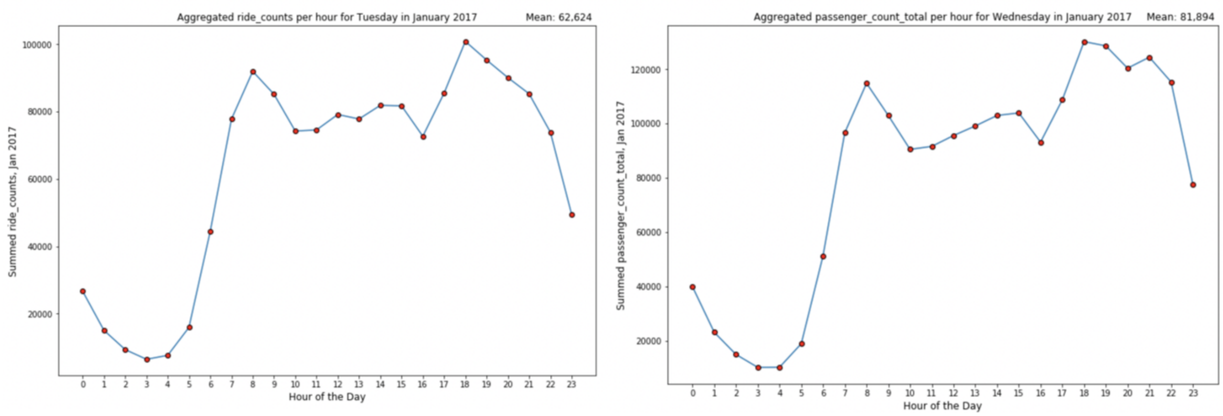


Figure 12: Aggregated Taxi ride counts and passenger counts on weekdays.

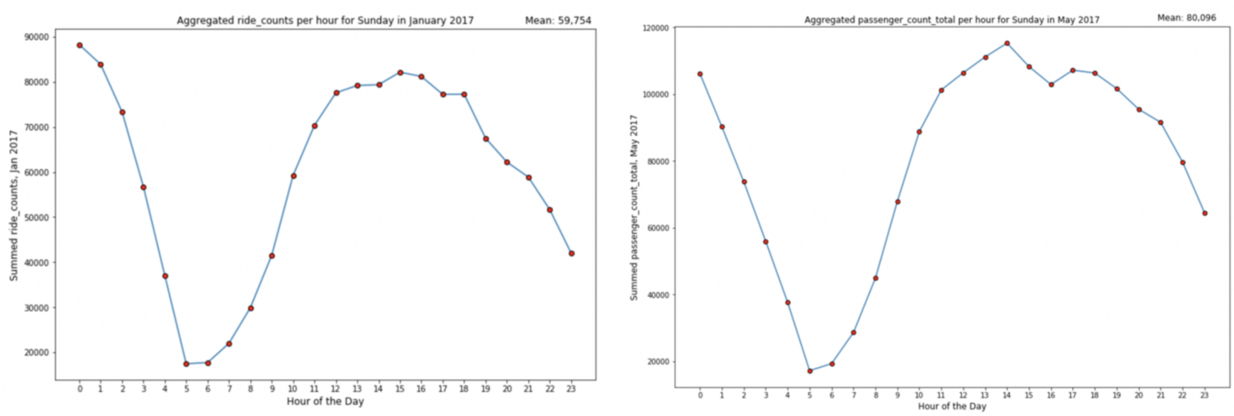


Figure 13: Aggregated Taxi ride counts and passenger counts on weekends.

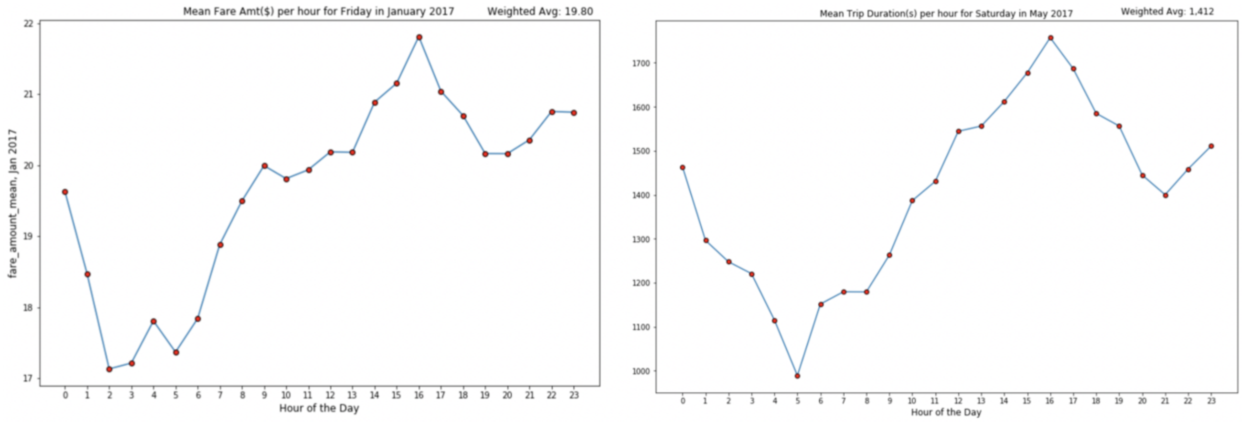


Figure 14: Mean Taxi Fare and Mean Trip Durations per hour.

For-Hire Vehicle (FHV) Data Exploration

To better understand the distribution of FHV and shared FHV trips, we analyzed the ridership trends of For-Hire vehicles by aggregating the total ride counts and the average trip durations for each hour of day and day of the week. Similar to taxi, the hourly rides for both shared FHV and total FHV are both higher during the morning and evening rush hours (Figure 15), but the evening rush hours have slightly more trips compare to morning hours. Trips in the afternoon (3 -4 pm) have longer durations, and trips during midnight are relatively shorter (Figure 16) based on the average trip durations. By comparing the trips count in days of the week, we found Fridays and Saturday have more total trips (Figure 17), and trips during weekends are shorter than the trips during weekdays(Figure 18). Finally, the choropleth maps (Figure 19) show the normalized rides count for each Pick up and drop off Taxi Zones (counts normalized by the area of zones), which we found the zones with high trip amounts(darker zones) are mostly concentrated at lower/middle Manhattan and downtown Brooklyn areas for both Pick up and Drop off locations. Such finding suggests that a large portion of our of our model simulations will be reflecting the trips in these areas, thus we need to be more carefully consider the regional demographic information of these areas as well as their functionalities (e.g. shopping, parks, etc), to avoid any false assumptions when profiling people choices. For comparison, the distribution of trip duration using public transportation (subway&bus) is also shown in Figure 20. The average commute time is 4530 seconds (roughly 75 mins).

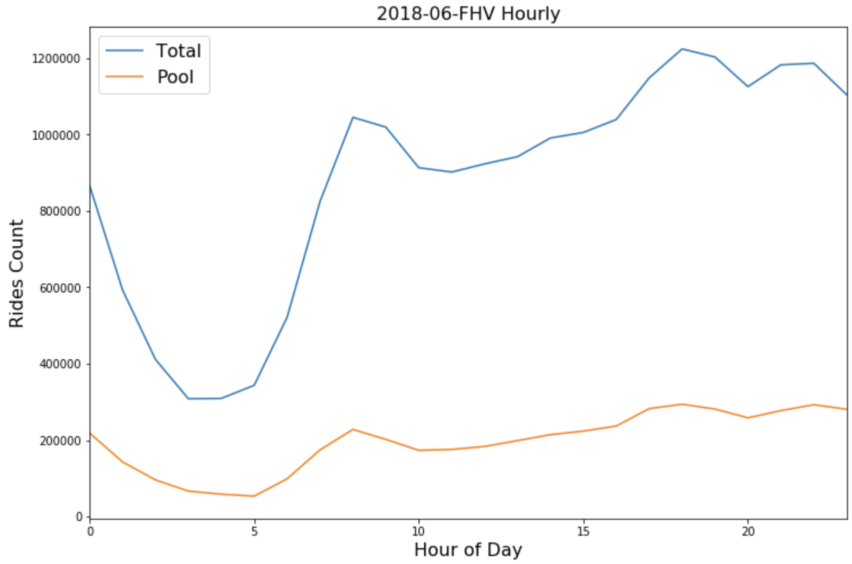


Figure 15: Hourly FHV Trips counts

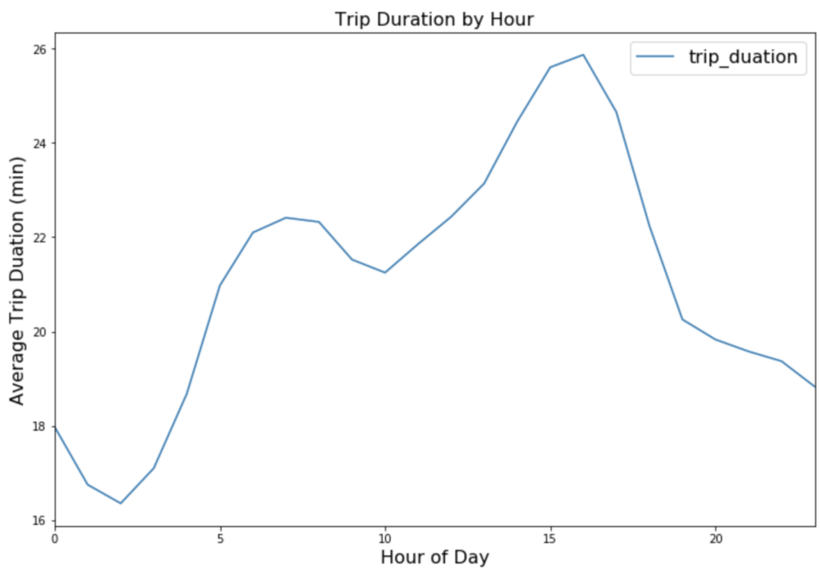


Figure 16: FHV Hourly average Trip Duration

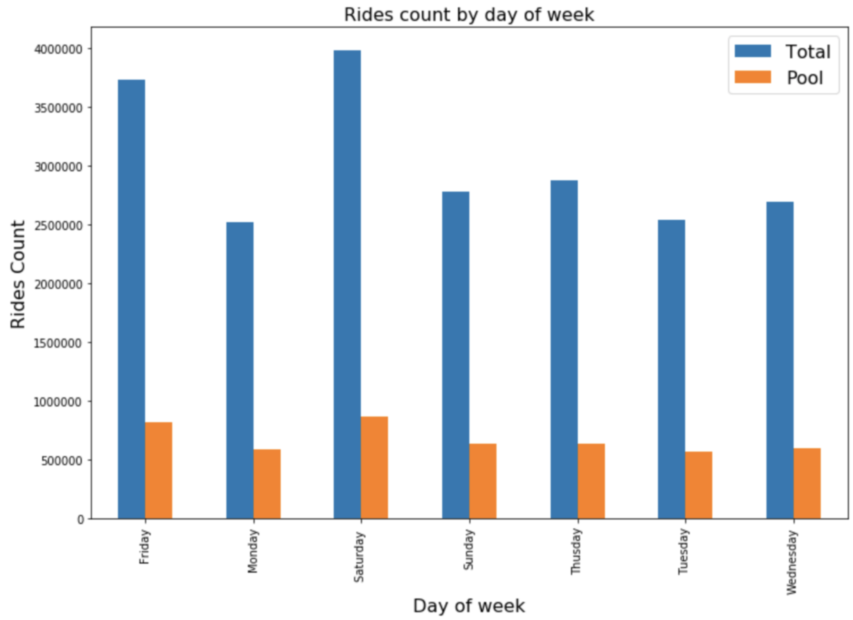


Figure 17: FHV Trips counts by day of week

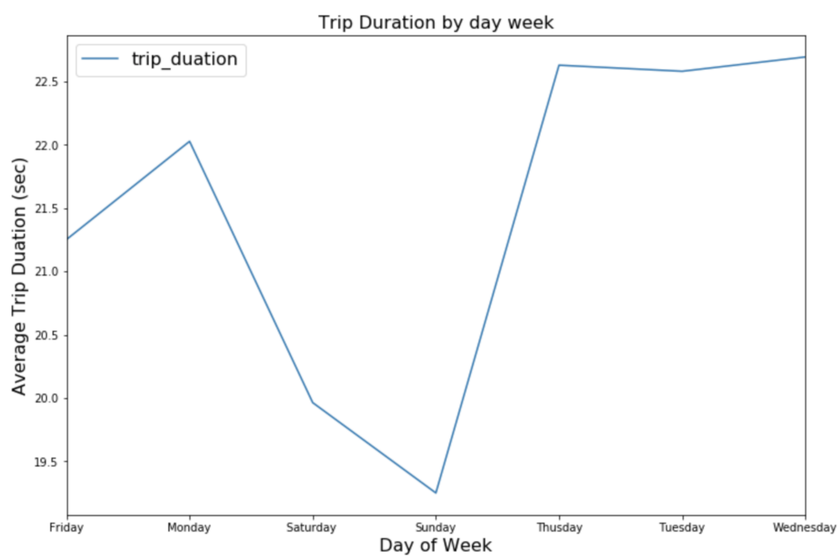


Figure 18: FHV average Trip Duration by day of week

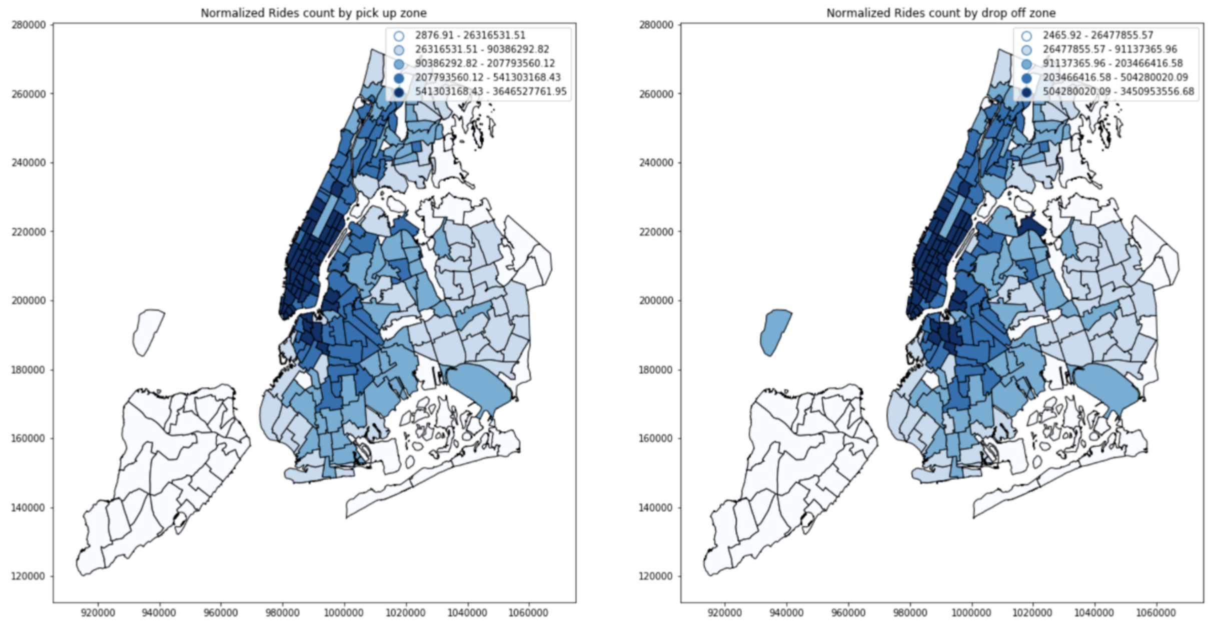


Figure 19: Pick up and drop off density per taxi zone

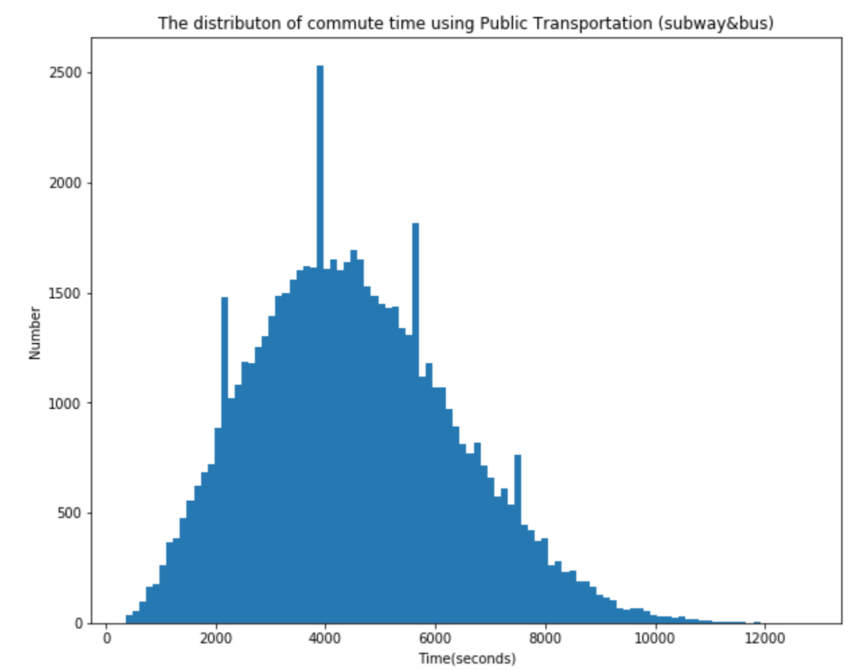


Figure 20: Distribution of trips by commute time

Methodology:

The probability of mode j given nest k, where j belongs to nest k:

$$P(y = j|y \in N_k) = \frac{e^{\frac{1}{\tau_k} V_j}}{e^{IV_k}} \tag{4}$$

The probability of nest k:

$$P(y \in N_k) = \frac{e^{\tau_k V_j}}{\sum_m e^{\tau_m IV_m}} \tag{5}$$

Conditional probability for mode j, which equals to the probability of mode j given nest k where j belongs to nest k, multiplies the probability of nest k.

$$P(y = j) = P(y \in N_k) \cdot P(y = j|y \in N_k) \tag{6}$$

References

Assembly, N. Y. S. (2019). *BILL NO A02009C*. Retrieved from https://www.nyassembly.gov/leg/?default_fld=&leg_video=&bn=A02009&term=2019&Summary=Y&Actions=Y&Committee%26nbspVotes=Y&Floor%26nbspVotes=Y&Memo=Y&Text=Y&LFIN=Y

Beria, P. (2016). Effectiveness and monetary impact of Milan's road charge, one year after implementation. *International Journal of Sustainable Transportation*, *Vol. 10*.

Capstone. (2018). Prediction of Mode Shift in New York City. Retrieved from https://cuspcapstones.github.io/Prediction-of-Mode-Shift-in-Cities-Based-on-Trip-Cost-Duration_2018/

DOT. (2018). *New York City Mobility Report*. NYC Department of Transportation. Retrieved from https://www1.nyc.gov/html/dot/downloads/pdf/mobility-report-2018-print.pdf

Eliasson, J., Hultkrantz, L., Nerhagen, L., & Rosqvist, L. S. (2009). The Stockholm congestion – charging trial 2006: Overview of effects. *Transportation Research Part A: Policy and Research*, *Vol. 43*.

Gibson, M., & Carnovale, M. (2015-2016). The effects of road pricing on driver behavior and air pollution. *Department of Economics, Williams College*.

Heiss, F. (2002). *Specification(s) of Nested Logit Models* (MEA discussion paper series No. 02016). Munich Center for the Economics of Aging (MEA) at the Max Planck Institute for Social Law and Social Policy. Retrieved from https://ideas.repec.org/p/mea/meawpa/02016.html

Lehe, L. (2019). Downtown congestion pricing in practice. *Transportation Research Part C: Emerging Technologies*, *Vol. 100*.

MTA. (2017). Introduction to Subway Ridership. *MTA.info*. Retrieved from http://web.mta.info/nyct/facts/ridership/

Pearce, A. (2018). How 2 M.T.A. Decisions Pushed the Subway Into Crisis. *The New York Times*. Retrieved from https://www.nytimes.com/interactive/2018/05/09/nyregion/subway-crisis-mta-decisions-signals-rules.html

Ramming, & Scott, M. (2002). *Network knowledge and route choice* (PhD thesis). Massachusetts Institute of Technology. Retrieved from https://dspace.mit.edu/handle/1721.1/49797

Repository, N. Y. U. S. D. (2010). *New York City Census Tract Population Centers*. Retrieved from https://geo.nyu.edu/catalog/nyu-2451-34504

Sobolevsky, S., Levitskaya, E., Chan, H., Postle, M., & Kontokosta, C. (2018). Impact Of Bike Sharing In New York City. Retrieved from https://arxiv.org/abs/1808.06606v1

Taxi, & (TLC), L. C. (2019). *NYC Taxi Zones.* NYC Open Data. Retrieved from https://data.cityofnewyork.us/Transportation/NYC-Taxi-Zones/d3c5-ddgc

Tong, Y. (2015). How New Yorkers Prefer to Take Public Transport? A Comprehensive Analysis Based on 2010-2011 Regional Household Travel Survey.

Train, K. (1977). A validation test of a disaggregate mode choice model. *ScienceDirect*, *Vol. 12*. Retrieved from https://www.sciencedirect.com/science/article/pii/004116477890120X

Yu, L., & Sun, B. (2012). Four types of typical discrete Choice Models: Which are you using? - IEEE Conference Publication. *IEEE*. Retrieved from https://ieeexplore.ieee.org/document/6273550

of Taxation, N. Y. S. D., & Finance. (2018). *Technical Memorandum TSB-M-18(1)CS*. Retrieved from https://www.tax.ny.gov/pdf/memos/cs/m18-1cs.pdf