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Spatial welfare effects of shared taxi operating policies for first mile airport access

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ABSTRACT

With increasing availability of alternative mobility options for first/last mile, it is necessary to better understand how shared taxis are impacting airport access demand and consumer surplus. However, no study has been conducted to evaluate the welfare effects of the range of shared taxi matching and fare allocation policies for airport access. Using several data sources primarily from Port Authority of NY and NJ and The Taxi and Limousine Commission, a mode choice model is estimated for access to John F. Kennedy International Airport in New York City. The baseline model and data show that passengers have a value of time of $101 per hour, consistent with Harvey's study from 1986. Airport taxi travelers are also elastic to cost in a similar manner to public transit. The model is used to evaluate two policies: a first (we call this wait-share policy) where taxis can offer shared rides for two passengers from the same zip code, incorporating an endogenous expected wait time variable; and a second (we call this space-share policy) where taxis match randomly arriving passengers from any zip codes in the city. These two policies reflect extreme ends of a spectrum of policies between waiting and detouring. Findings suggest that having a shared taxi option benefit passengers in NYC going to JFK airport by at least 10% increase in consumer surplus. However, the increase in taxi ridership comes at a cost to transit ridership. Furthermore, the population in NYC that benefits most is highly dependent on the type of shared taxi policy. A wait-share policy benefits passengers from the dense parts of Manhattan most, while a space-share policy distributes the benefits more to other boroughs. These insights can help policymakers set regulations in providing first/last mile ride-sharing taxi options in different cities around the world.

Introduction

First and last mile travel refers to the portions of a trip to access or egress from the main line haul transport (Chang and Schonfeld, 1991; Li and Quadrifoglio, 2010; Djavadian and Chow, 2017a). The quality of last mile trips can significantly impact the main line haul trip, whether it is freight deliveries, public transit, or long distance travel. For example, Bower (1976) found that demand for air travel itself is elastic with respect to access costs to reach the airport. In other words, poor

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access can reduce the demand for air travel itself. And with rising urbanization (WHO, 2010), the importance of first and last mile access to air travel is expected to continue to grow.

In the case of access for air travel, there are a number of modes used. A key mode in addressing this first mile problem is the taxicab. According to the Port Authority of New York and New Jersey (PANYNJ), the proportion of taxi mode of travelers in New York City (NYC) accessing John F. Kennedy (JFK) Airport (PANYNJ, 2014) from 2010 to 2014 was 31%, while other for-hire-vehicles (FHV) were 11%, for a total of 42% share. Considering that JFK is the fifth busiest airport in the U.S. (FAA, 2016), this is indicative of the role of taxi and other FHVs as a first/last mile access mode for air travel.

However, our understanding of the role of taxis in this capacity has changed in recent years because of new mobility services enabled by information and communications technologies (ICTs). Ridesharing and ridesourcing services, such as Uber (Lazo, 2016), Lyft (Hawkins, 2015), and Via (Schifman, 2016), offer new access options to travelers. These operations use mobile devices to hail rides, match rides, and split ride fares in the case of dynamic *shared taxi* trips.

It is therefore important for policymakers to have a better grasp of how taxi sharing options impact the consumer surplus of airport access travelers. By "consumer surplus", we refer to the overall utility gained by travelers to access an airport. Some studies, such as Yang and Yang (2011), consider social welfare for a taxi market which includes the costs of operating the taxi fleet. Since our interest is only on the social impact of different taxi operating policies (as opposed to the equilibration of taxi supply and demand in a taxi market), we ignore costs of operating taxis in this study and focus on consumer surplus. Do policies focusing more on matching at a fixed location lead to higher consumer surplus than policies involving en-route matching? How do welfare impacts differentiate over space and proximity to the destination airport?

In this study, we propose to study these research questions. We use JFK airport access survey data to model the demand and consumer surplus for access modes under a base scenario involving only solo taxis. Two shared taxi policies are then evaluated and compared against this base scenario. The two policies represent extreme cases of shared taxis: one involving matching passengers at the same location with no detour but unconstrained by wait time, and one involving matching simultaneously arriving passengers at random zones in the system. To the best of our knowledge, there is no behavioral study on the impact of shared taxi technology on the consumer surplus of travelers, much less of airport access travelers. Insights from this research can support policies for first and last mile ride-sharing taxi operations in cities around the world.

The remainder of this paper is organized as follows: Section "Literature Review" presents a literature review on taxi evaluation models and shared taxi operational policies; Section "Experimental Design and Data" introduces the experimental design and data; Section "Mode Choice Model" presents a model estimated from the JFK survey data; Section "Policy Analysis" shows the scenario analysis for the two extreme policies, and section "Conclusion" is the conclusion.

Literature review

There are a wide number of studies on evaluating taxi performance. Some of the earliest analytical studies on taxis (Daganzo, 1978; Daganzo et al., 1977) are based on continuous mathematical models to relate system performance to demand and service area. However, the demand is not dependent on that performance. More recent efforts, including Yang and Wong (1998) and Yang et al. (2010), developed economic equilibrium models that capture the costs of matching taxi drivers to customers.

Taxi studies pertaining to airport pickup and drop-off are also abundant. Several studies look at taxi pickups at airports with queueing models to evaluate different operating policies (Curry et al., 1978; da Costa and de Neufville, 2012; Yazici et al., 2016). These studies do not seek to explain access travel behavior.

Harvey (1986) published one of the first explanatory models on airport access mode choice, noting the difference in preference due to different trip purposes. A single generalized cost variable was used with an assumed value of time. Tam et al. (2005) and Choo et al. (2013) estimated mode choice models for Hong Kong and Seoul, respectively. Hess et al. (2013) estimated a joint model of airport, airline, and access mode choice using a stated preference survey of U.S. east coast airports. Yang et al. (2014) focused on a specific subset of origin-destination (OD) pairs and analyzed variations in travel times and cost that arise due to traffic conditions and party size. Yazdanpanah and Hosseinlou (2016) associated personality traits with the access mode choice. None of these studies considered airport access mode choice with shared taxi mode.

There have been a number of studies on social impacts of shared taxis. Rayle et al. (2016) provided a policy study comparing taxi with shared mobility. Paraboschi et al. (2015) evaluated shared taxi as a two-sided market. Several studies have been based on simulation evaluations of system performance (Djavadian and Chow, 2017a,b; Agatz et al., 2011; D'Orey et al., 2012; Maciejewski and Nagel, 2013; Jung and Jayakrishnan, 2014; Jung et al., 2014; Martinez et al., 2015). Al-Ayyash et al. (2016) proposed a demand model for shared taxis for students commuting to University of Beirut in Lebanon. No study has yet been conducted to evaluate the welfare effects of shared taxis' operations to access airports and other similar first or last mile destinations.

In shared taxi operations, several different policies need to be considered by the operator. One is how to match customers together in a shared ride, which is a culmination of decisions on centralized versus distributed operations (d'Orey et al., 2012), ride hailing technology (He and Shen, 2015), and idle vehicle positioning strategy (Yuan et al., 2011). Some services may match only customers within proximity of one another, perhaps waiting up to a threshold time for the passenger requests. Other services may match based on en-route detours of the first pickup, up to a certain maximum detour, to pick up a second passenger. For dynamic ridesharing, pairing typically does not exceed two passenger groups. On the matching problem, Wang et al. (2014) propose a stable matching framework to find matches between passengers and vehicles. While not a taxi study, Jorge et al. (2015) provide an interesting study of airport access using carsharing services which emphasizes the importance of rebalancing vehicles to improving likelihood of successful customer-vehicle matches.

A second policy is fare allocation; an appropriate sharing mechanism should ensure fairness between passengers who either have to experience longer detours or wait times, and to discourage passengers from trying to game the system. Furuhata et al. (2015) examine different cost sharing mechanisms in designing online fare allocations, and propose a proportional online cost sharing mechanism to ensure fairness. Gopalakrishnan et al. (2016) consider the concept of "sequential" fairness. Tao and Wu (2008) provide an overview of different types of shared taxi services. Furuhata et al. (2013) further provide taxonomy of different dynamic ridesharing operating policies, considering matching methods and fare allocation.

We contribute to this literature with a first empirical study of the welfare effects of shared taxi operation as an airport access mode. We also make a methodological contribution, as we define two shared taxi operating policies representing extreme ends of a spectrum of matching and fare allocation decisions. We argue that shared taxi operating policies fall somewhere within this spectrum, and evaluate the spatial welfare effects of each policy using New York City access to JFK airport as a case study.

Experimental design and data

Experimental design

The objective of the experiment is to fit a mode choice model for accessing JFK airport via taxi, and then to modify the explanatory variables in the model utility function to evaluate different shared taxi policies and the spatial welfare effects. Given the number of matching policies out there, we propose to study two extremes of the spectrum. Consider Fig. 1, which illustrates the trade-offs made among the spectrum of matching policies. On the left end, policies of this type match passengers to each other based on the same location. The arrival of the latter passenger is a random wait time dependent on the arrival demand at that location. Busier locations will tend to prefer this strategy. There are no detours, but wait time is unconstrained. We call this the "wait-share" matching policy. On the right end, two passengers are grouped when they call in simultaneously (or nearly so), regardless of their locations. The further away passenger is picked up first, and is detoured to pick up the second passenger on the way to the airport. There is no wait time, but detours are unconstrained. We call this the "space-share" matching policy.

In practice, shared taxis operate at some point between the two. However, if we can evaluate the two extreme matching policies and compare their welfare effects, we can extrapolate insights into the whole spectrum of matching policies. To be clear, we do not claim that exploring two extreme policies would allow us to interpolate welfare effects for the whole range of the spectrum. This cannot be done because welfare effects are nonlinear. Evaluating additional policies within the spectrum is possible, but would require coding and running new routing algorithms (e.g. Jung and Jayakrishnan, 2014) or multi-agent decision rules (e.g. Martinez et al., 2015). This may be helpful to policy-makers, but given the nonlinear nature of the welfare effects, the benefits of each analysis would be localized to that portion of the spectrum. Instead, this study presents a novel approach to gain broad insights into opposing policies for a megacity in a computationally cheap and elegant manner, and to provide guidelines for replicating similar analyses in other regions. Future research can look more specifically at different instances within the spectrum. Even more advanced dynamic data-driven switching strategies (e.g. Guo et al., 2017) may be considered by operators.

For fare allocation between users, we adopt a proportional cost sharing mechanism (see Furuhata et al., 2015) based on travel times. In the case of the wait-share policy, the proportional cost sharing simplifies into an equal 50–50 split. For two passengers at zone i and zone j, where $tt_i > tt_j$ are the travel times to the airport, a proportional fare allocation would be to assign $\frac{tt_{i,j}+t_j}{tt_{i,j}+2t_j}$ to the passenger at zone i and the remainder of the total fare to the passenger at zone j, where $tt_{i,j}$ is the travel time from zone i to zone j.

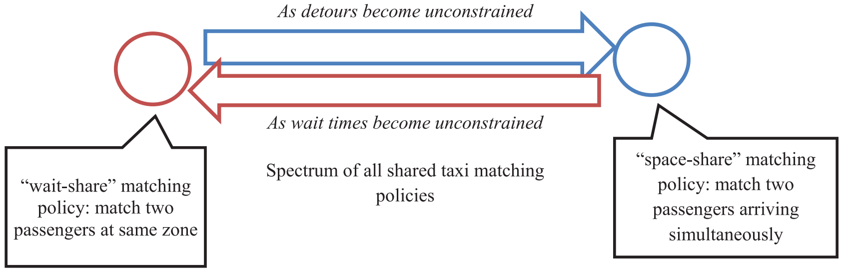


Fig. 1. Spectrum of matching policies capped by two extremes: a wait-share and a space-share policy.

A multinomial logit (MNL) model is estimated for solo taxi mode choice, shown generally in Eq. (1).

$$P_n(i|C_n) = \frac{\exp(V_{in})}{\sum_{j \in C_n} \exp(V_{jn})} \tag{1}$$

where P_n is a conditional probability of person n choosing an alternative i given the availability of choice set C_n, and V_{in} is the representative utility for alternative i to person n. Based on this model, we obtain a utility function for each sampled passenger n with a cost variable included as f_n.

Based on this model, several outcomes can be inferred from the baseline scenario. A welfare measure can be determined by the logsum expression in Eq. (2) (Small and Verhoef, 2007), where α_n is the marginal utility of income for passenger n and CS_n is the consumer surplus of passenger n.

$$E[CS_n] = \frac{1}{\alpha_n} \ln \sum_{i \in C_n} \exp(V_{in}) \tag{2}$$

In the case where policy changes involve small changes in consumer surplus per person relative to income, an average value α can be assumed (see de Jong et al., 2007). This measure can be summed up across the population to obtain the relative consumer surplus for this set of choices, $E[CS] = \sum_n E[CS_n]$. When considering relative difference between two scenarios (e.g. $\frac{CS_{new} - CS_{old}}{CS_{old}}$), this average value will drop out, so for our calculations we will assume $\alpha = 1$. The resulting measure is unitless; it represents the expected utility that a person gets from the set of choices presented to them, which derives this expression assuming the unobservable attributes belong to independent Gumbel distributions. While the value of CS alone is meaningless in this case, it is possible to determine relative changes in consumer surplus between two scenarios. Relative comparisons using this logsum measure have been made in prior studies in the literature (for example, see Niemeier, 1997); relative measures of changes in consumer surplus between different scenarios have also been made in the transportation economics literature (see Arnott and Inci, 2006; Amer and Chow, 2017).

Taxi sharing policies can then be evaluated in terms of this logsum welfare measure relative to the baseline scenario. Under the two shared taxi matching policies, the cost variable is altered as follows.

Wait-share policy

For the wait-share matching taxi policy, we assume that taxis have the option to operate as a shared service for two different passengers coming from the same zip code. A passenger is equally likely to be the first or the second pickup. If they are the second, there is no additional wait time. If they're the first, however, the effective fare for a traveler is half the original fare plus the expected cost of additional waiting to match up with another passenger, $E[W_n]$. If the original taxi fare for an observation n is defined by f_n, then the new effective fare is defined by Eq. (3).

$$f'_n = \frac{f_n}{2} + E[W_n] \tag{3}$$

The expected cost of waiting (converted to units of cost) is defined as shown in Eq. (4).

$$E[W_n] = 0.5(0) + 0.5(1.76)\left(\frac{\bar{v}}{p_s \lambda_n}\right) \tag{4}$$

where $\bar{v}$ is a median value of time, λ_n is the number of arrivals per unit time in the zip code of observation n, and 1.76 is a wait time premium (Balcombe et al., 2004). The wait time premium is used to account for the fact that travelers tend to psychologically value 1 min of wait time much higher than 1 min of time spent in motion. From empirical studies, Balcombe et al. (2004) found that 1 min of wait time is equivalent to 1.76 min of in-vehicle travel time. The term $0.5(0)$ refers to the equally likely probability of being first and not having to wait. The term $(1/\lambda_n)$ is the expected inter-arrival time for a particular time of day, assuming taxi pickup arrivals are Poisson-distributed (Sayarshad and Chow, 2016). The value p_s is an endogenous fraction of the taxi population that prefers shared taxi over single passenger taxi. For instance, if a taxi and passenger are waiting for a second passenger, the next arrival may not be interested in shared taxi. A fixed point estimation method is proposed to obtain this value of p_s.

Space-share policy

For the space-share matching policy, we assume that taxis match two passengers at different zones in the network. For a region with high demand for taxis to the airport, we assume for the purpose of zone-to-zone matching that there is no wait time for either passenger, i.e. they both would arrive (or pre-arrange) such that the only additional cost is from having a detour for the first passenger. For example, a person requesting a taxi to the airport in a zone in Upper West Side of Manhattan may be matched with a customer in Downtown Brooklyn on the way to the airport. The person picked up first at Upper West Side would encounter an additional travel cost due to the detour to pick up the passenger in Downtown Brooklyn. We introduce a function $z(n) \in Z$, which maps a passenger to their zone. For general study areas, Z is a set of all paired zones that requires exhaustive vehicle routing algorithms to sequence the zones to minimize detours.

Conveniently enough, the study area for our analysis is NYC yellow taxis and JFK airport, as shown in Fig. 2. Since JFK airport is actually located at the southeast corner of the region, we can significantly simplify the sequencing by using a simple ranking by distance from the airport, i.e. $z = 1$ is the closest zone to the airport, while $z = |Z|$ is the furthest. For this policy, we assume that the further zone is always picked up first. The probability of a randomly arriving passenger being first or second is determined by summing the arrival rates for all zones of the other passenger j ranked higher ($j > z(n)$) and lower ($j < z(n)$), as shown in Eq. (5).

$$f'_n = \frac{\frac{\lambda_z}{2} + \sum_{i=1}^{z(n)-1}\lambda_i}{\sum_{i=1}^{|Z|}\lambda_i} f'_{n1} + \frac{\frac{\lambda_z}{2} + \sum_{i=z(n)+1}^{|Z|}\lambda_i}{\sum_{i=1}^{|Z|}\lambda_i} f'_{n2} \tag{5}$$

where λ_z refers to arrival rates for a given zone $z(n)$ such as a zip code in NYC; f'_{n1} is the expected cost if passenger n is first; and f'_{n2} is the expected cost if the passenger is second. Given that the passenger is first, the expected cost is weighted for a second passenger in each zone j, $j < z(n)$, and the effective change in detour time, $t_{zj} + t_j - t_z$, and proportional fare splitting, $f_z\left(\frac{t_{z,j}+t_j}{t_{z,j}+2t_j}\right)$. t_{zj} is the travel time from zone $z(n)$ to zone j, t_j is the travel time from a zone j to the airport, and f_z is the fare that would have been assigned to the first passenger, assumed to be the same fare as the solo passenger case.

The incentive for the taxi driver to allow sharing in this case is to increase the demand for service, which reduces their idle time despite serving a longer route than directly going from $z(n)$ to the airport. Other adjustments to fleet size may occur as well; since the study is focused on the impact of travelers only, this is only to point out a justification for such a policy. We do not consider supply side costs or market adjustments. The expected cost for a first passenger is shown in Eq. (6), taking into account the likelihood of two passengers being drawn from the same zone under this policy.

$$f'_{n1} = \frac{\frac{\lambda_z}{2}\left(\frac{f_z}{2}\right)}{\frac{\lambda_z}{2} + \sum_{i=1}^{z_n-1}\lambda_i} + \sum_{j=1}^{z_n-1} \frac{\lambda_j\left(\bar{v}(t_{zj} + t_j - t_z) + f_z\left(\frac{t_{zj}+t_j}{t_{zj}+2t_j}\right)\right)}{\frac{\lambda_z}{2} + \sum_{i=1}^{z_n-1}\lambda_i} \tag{6}$$

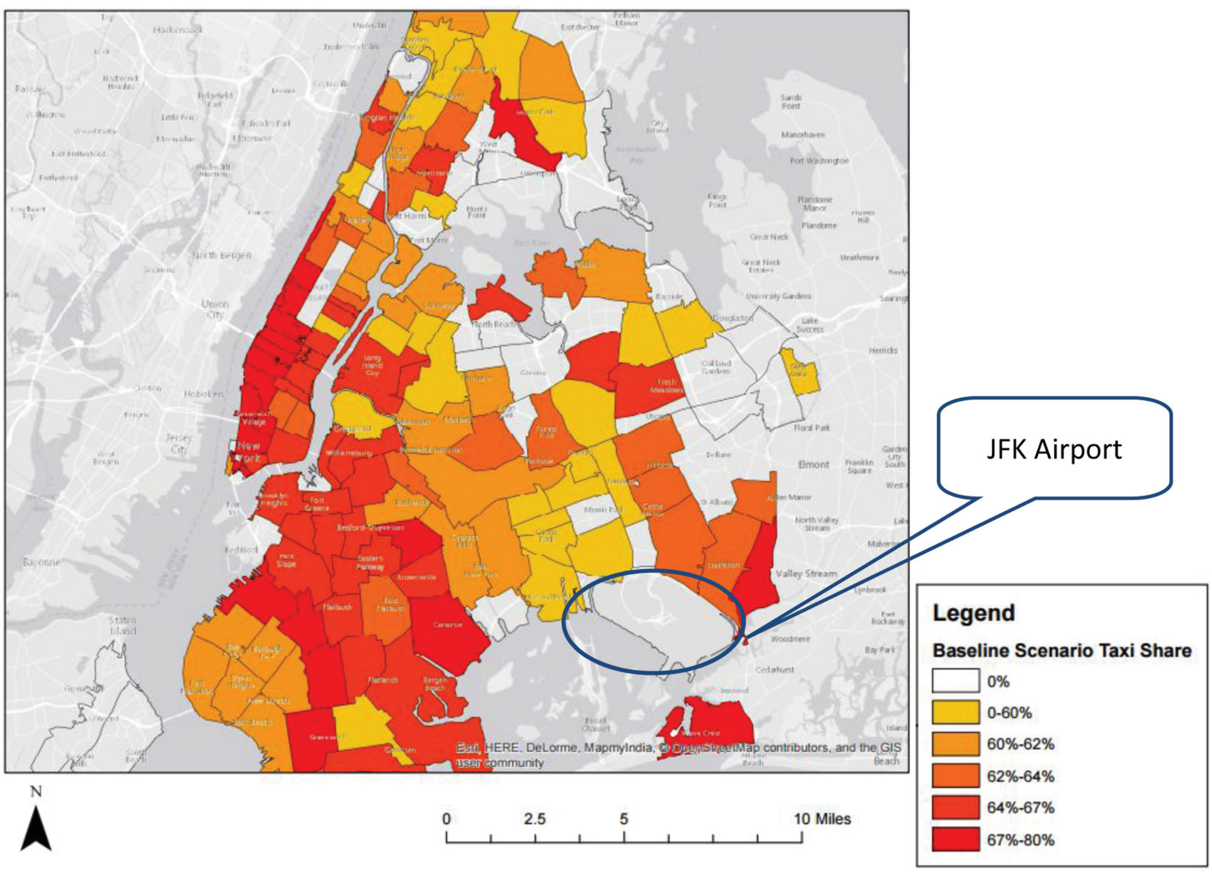


Fig. 2. Taxi mode by origin zone for the study area in ArcGIS.

If the passenger is second to be picked up, then their cost is shown in Eq. (7).

$$f'_{n2} = \frac{\frac{\lambda_z}{2}\left(\frac{f_z}{2}\right)}{\frac{\lambda_z}{2} + \sum_{i=z_n+1}^{|Z|}\lambda_i} + \sum_{j=z_n+1}^{|Z|} \frac{\lambda_j\left(f_j\left(\frac{t_z}{t_{jz}+2t_z}\right)\right)}{\frac{\lambda_z}{2} + \sum_{i=z_n+1}^{|Z|}\lambda_i} \tag{7}$$

Compared to the wait-share policy, the space-share policy is much harder to achieve in a dynamic setting without some actual wait time. Realistic implementation of space-share would probably involve pre-arranged calls where passengers would be scheduled to depart from their origin without having to wait outside, for instance. Nonetheless, its analysis can provide useful insights into boundary conditions of such policies.

Data

The main data source used is the PANYNJ's (2014) Annual Customer Satisfaction survey. Every year, the Port Authority conducts a comprehensive survey of its customers at JFK, Newark Liberty International, LaGuardia, Stewart International, and Atlantic City International airports. Customers are asked about a host of topics and the survey questions vary from year to year, although questions about the ground portion of their itinerary are always included. The compiled survey data from each year between 2010 and 2014 contains 25,616 records.

Because of the need to evaluate the space-share policy, we require a data set of passengers arriving to JFK airport for departure and who provided a NYC zip code for the origin of their trip. We also leave out the passengers who have access to effectively free travel modes due to business or hotel arrangements. In order to make use of the larger pool of data for model estimation purposes, we separate the data into two portions, as summarized in Table 1. After dropping the free travel mode observations, the mode share of taxi and FHV increases from 42% to approximately 65% of the remaining 4023 samples.

For this larger set, we imputed the zip code information and used that to estimate a JFK airport access mode choice model. A subset of these data that include specified zip codes is used for validation and analysis of the policies. After this filtering, the subset contained 906 records. The percent visitors drop drastically from the larger set to the subset because the individuals who do not provide information on zip code of origin are likely the visitors who do not have the zip code information available.

The study area is shown in Fig. 2, which illustrates all the zip codes of survey respondents' origins in the subset of data for analysis. Travel times and distances are drawn from the 199 zip code centroids using Google Maps API.

We used other data sources to supplement the PANYNJ (2014) data. Although zip codes were used as trip origination zones, they are not polygonal areas but rather collections of lines and points. To assist with analyses using spatial aggregation, Zip Code Boundaries are published by the New York City Department of Information Technology & Telecommunications (DoITT). Zip code boundaries were obtained from NYC Open Data (2016).

Because the Annual Customer Satisfaction survey does not contain questions pertaining to cost of transportation, other data sources were included to estimate some variables. The New York City Taxi and Limousine Commission releases records for all trips made by yellow taxis and so-called "Street Hail Livery" taxis (TLC, 2015). Useful elements are latitude and longitude of the origin and destination, trip distance and fare. To extract only trip records ending at JFK airport, the drop-off latitude and longitude are filtered using a bounding rectangle covering all airline terminal areas and roadways, as shown in Fig. 3. The arrival rates per hour were estimated by dividing total one month taxi pickups per zip code from TLC (2015) by 31 days and 24 h.

To summarize the trip data by zip code as averages of fare, travel time, and pickup location, the origination latitude and longitude are intersected with the Zip Code Boundaries shapefile. Fig. 4 shows a choropleth for two data elements in each zip code. The estimated travel time by transit is shown as the shade of color, and the single point is a geographical centroid for all the origin latitude/longitude data of trips extracted from TLC (2015).

Transit travel times from each origination zone were obtained from queries to the Google Maps API (maps.googleapis.com) Directions Service. The same weekday peak-hour was specified as the departure time in each query; transit travel times to JFK airport vary minimally at different hours of the day, with the exception of longer times during overnight hours (Yang et al., 2014).

Table 1
Summary of PANYNJ (2014) Annual Customer Satisfaction Surveys.

Description	Data set for estimation	Subset of data for analysis
Sample size	4023	906
Number choosing taxi or FHV (% of sample)	2629 (65.3%)	548
Number choosing transit	909 (22.6%)	227
Number choosing other paid alternatives	485 (12.1%)	131
Average taxi travel time (minutes)	37.31	36.21
Average taxi fare	$61.76	$60.78
Average transit travel time (minutes)	67.46	70.00
Percent visitor	63.7%	35.8%

Fig. 3. Reported locations in the TLC (2015) data that are within the bounding rectangle used to filter JFK trips.

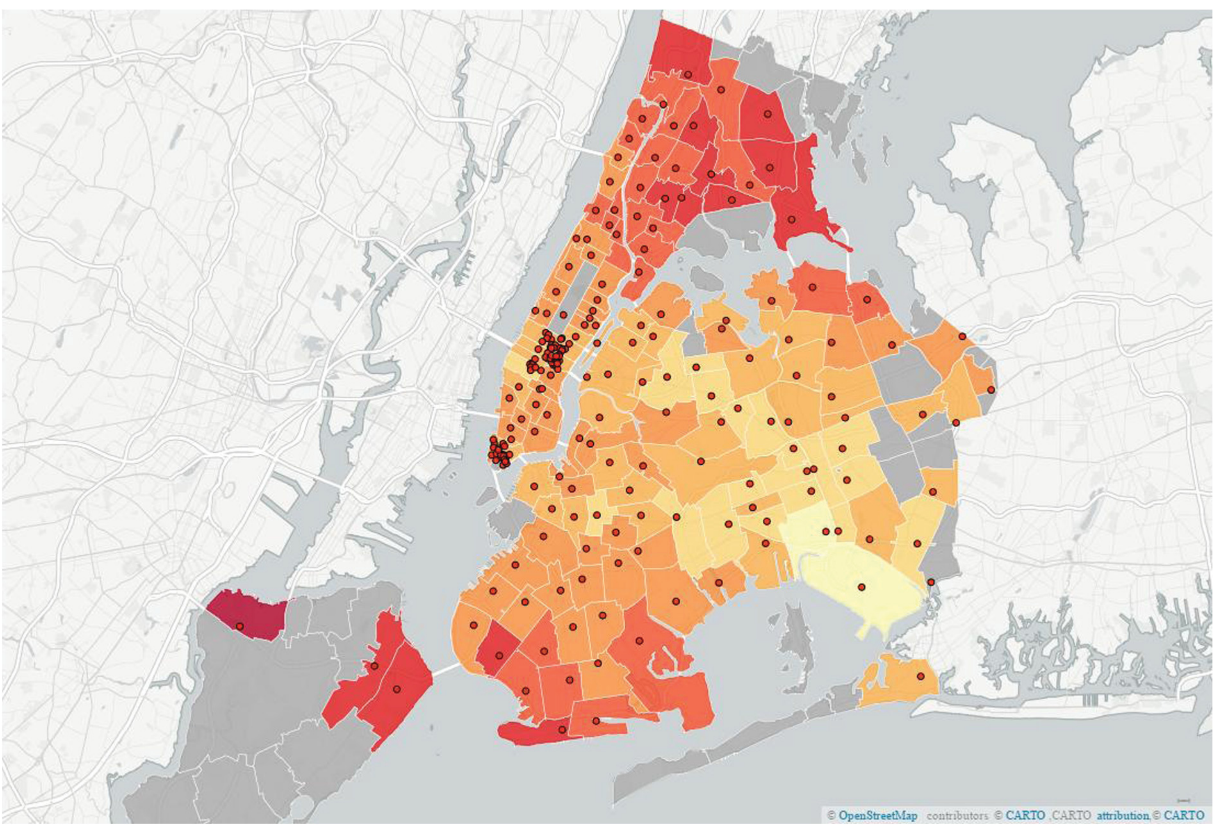


Fig. 4. Choropleth of transit travel times (via zone shading) and centroid locations from TLC (2015).

Based on these data, there are two comparable measurements between TLC and PANYNJ data sets. The first is the number of taxi trips overall. The Port Authority reported that 286,500 taxis were dispatched to JFK in October, 2015 (PANYNJ, 2015). The TLC data, filtered using the latitude-longitude bounding rectangle, contains 274,922 records. Some error is expected due to noise in the GPS coordinates, with many pickup points being reported on roadways exiting the airport.

The second is the estimated travel time. Some surveys contained a question about travel time to airport. When answered, these data were compared to the estimates generated by the aggregated TLC data and the Google Maps query for the same zone. The median travel time reported by customers who used a taxi or for-hire vehicle was 40 min, and the median estimate based on averaging TLC trips data for the same zones was 37.9 min. The median travel time reported by customers who used transit was 60 min, and the median estimate based on Google Maps queries for the same zones was 66.7 min. In some years, the survey only accepted answers in increments of 5–30 min, so the difference between the two medians does not necessarily indicate any bias. In general, the set of self-reported travel times had a much higher standard deviation than the set of estimates, which contained only one estimated value for each mode and zone.

For the value of time, a ratio of cost to travel time was computed for all trips. The median value was $\bar{v} = \$1.69/minute$ (or \$101.4/hr). By comparison, the marginal cost of time suggested by Yang et al. (2014), of \$57/hr for JFK trips, is significantly lower. However, the value of time suggested by combining the cost and time coefficients in the Harvey (1986) study was \$41.61 per hour, presumably at the nominal value of currency when the survey was performed in 1980. Adjusting that using the Bureau of Labor Statistics Consumer Price Index to our survey time period (2010–2014) results in \$111 to \$119, which is in the same order of magnitude as our estimated value. As a result, and to be more conservative, we keep our estimated value as the value of time. A sensitivity analysis is conducted in Section "Sensitivity Analysis" to verify the stability of the findings based on these values.

Mode choice model

Model estimation

Several different MNL models were estimated from these data. In the estimation phase, three alternatives were considered: a taxi alternative that also covers FHVs, a transit alternative for people who choose to take a \$2.75 subway ride and then transfer to a \$5 AirTrain ride, and lastly an "other" alternative for all other paid options (driving and parking long term, rental car, hotel shuttle service, etc.). These modes seem quite different at first glance, but they share one thing in common: pre-arranged, personally available access to the airport that not everyone in the population may have. Since the estimated model is not designed to infer any relationships with explanatory variables pertaining to these modes, it does not matter that they are lumped together as long as the resulting coefficients estimated from the specified utility function are statistically significant (which they are). The "other" alternative is assumed to have an average flat cost of \$20.

The best fitting model is reported in Table 2, based on ρ^2 value ("McFadden R^2", a measure of model fitness based on ratio of likelihood values before and after estimation), and statistical significance of parameters estimated. The model uses a cost variable (*COST*, in \$) for the taxi and transit alternatives. The cost parameter was found to have a negative sign and was statistically significant. It also includes a travel time variable for taxi (*TT*, in miles), which was also found to be significant.

The positive coefficient for *TT* can be justified by the fact that all the trips are being made to the airport, so there is no negative effect of distance aside from cost. Instead, the distance or travel time to the airport results in relative effects on choice between taxi, transit, and other personally available options through the use of separate variables *TT*1 and *TT*3. In

Table 2
Estimated MNL model.

Parameters	Value	Std. error	*t*-Test	*p*-Value
ASC_{OTHER}	−1.78	0.334	−5.33	<0.01
ASC_{TAXI}	0.495	0.183	2.70	0.01
B_{BAG}	0.647	0.106	6.13	<0.01
B_{BIZ}	0.517	0.0851	6.07	<0.01
B_{COST}	−0.0125	0.00458	−2.73	0.01
B_{TT1}	0.0313	0.00701	4.47	<0.01
B_{TT3}	0.0243	0.00728	3.33	<0.01
Model fitness				
Num. obs.	4023			
ρ^2	0.220			
$\bar{\rho}^2$	0.218			
LL(0)	−4419.717			
LL(B)	−3449.329			
Utility functions				
$V_{TAXI} = 0.495 - 0.0125 \times COST_{TAXI} + 0.0313 \times TT_{TAXI} + 0.517 \times BUSINESS$				
$V_{TRANSIT} = -0.0125 \times COST_{TRANSIT} + 0.647 \times NOBAGS$				
$V_{OTHER} = -1.78 + 0.0243 \times TT_{OTHER}$				

other words, the positive sign suggests that people further away from the airport will tend to prefer taxi or other personally available options over transit.

In addition to *COST* and *TT*, other explanatory variable included in the model specification is: a dummy variable for whether the trip is for business purpose ($BUSINESS = 1$) and whether the passengers have no check-in luggage ($NOBAGS = 1$). With a $\bar{\rho}^2 = 0.218$ and all parameters statistically significant at the 1% level, the model is considered an adequate fit, especially for explanatory purposes.

Model validation and baseline analysis

As this is an explanatory modeling effort, the focus of the validation is to ensure that the subset of data representing the baseline scenario can be accurately modeled in aggregate. We test this by comparing the observed mode shares to the model estimates in Table 3. The results show that absolute percentage point errors are within 5%.

For the 906 individuals observed in this sample, the total consumer surplus for this set of airport access mode choices is estimated to be 1297.64, which is 1.43 per person.

We can also evaluate the elasticity of the taxi choice to the two attributes in its utility function, using Eq. (8) (Ben-Akia and Lerman, 1985).

$$e_{(P_n(i)|x_{ink})} = (1 - P_n(i))\beta_{ik}x_{ink} \tag{8}$$

where x_{ink} is the k^{th} attribute of alternative i pertaining to individual n, β_{ik} is its parameter, and $e_{(P_n(i)|x_{ink})}$ is the elasticity. For the baseline scenario, the average elasticity across the 906 individuals of taxi choice with respect to cost is −0.27, with a range of −0.05 to −0.53. These suggest that the demand for taxi is on average inelastic to this variable, and similar in value to the −0.33 elasticity of transit demand with respect to transit fares (Curtin, 1968).

Policy analysis

Handling shared taxi as an alternative

With the baseline model estimated, we apply it to evaluate the two shared taxi policies. A nest is created for the taxi mode to introduce two branches: solo taxi and shared taxi. We don't have nested choice data to estimate the parameters as part of a nested logit model. However, since shared taxi and solo taxi have very similar characteristics, we assume that the same estimated parameters can be used to determine the preferred alternative among the two as the maximum utility, assuming the unobservable residual ε_{in} is independent of this conditional choice within the nest and remains the same regardless of which type of taxi mode is chosen. Utility of the taxi mode relative to transit and other modes is therefore now determined by Eq. (9), where f_n is the original taxi fare and f'_n is the shared ride fare plus expected wait time in units of dollars as shown in Eq. (1).

$$\begin{aligned} V_{TAXI,n} = \max(&0.495 - 0.0125 \times f_n + 0.0313 \times TT_{TAXI} + 0.517 \times BUSINESS, 0.495 - 0.0125 \times f'_n + 0.0313 \times TT_{TAXI} \\ &+ 0.517 \times BUSINESS) \end{aligned} \tag{9}$$

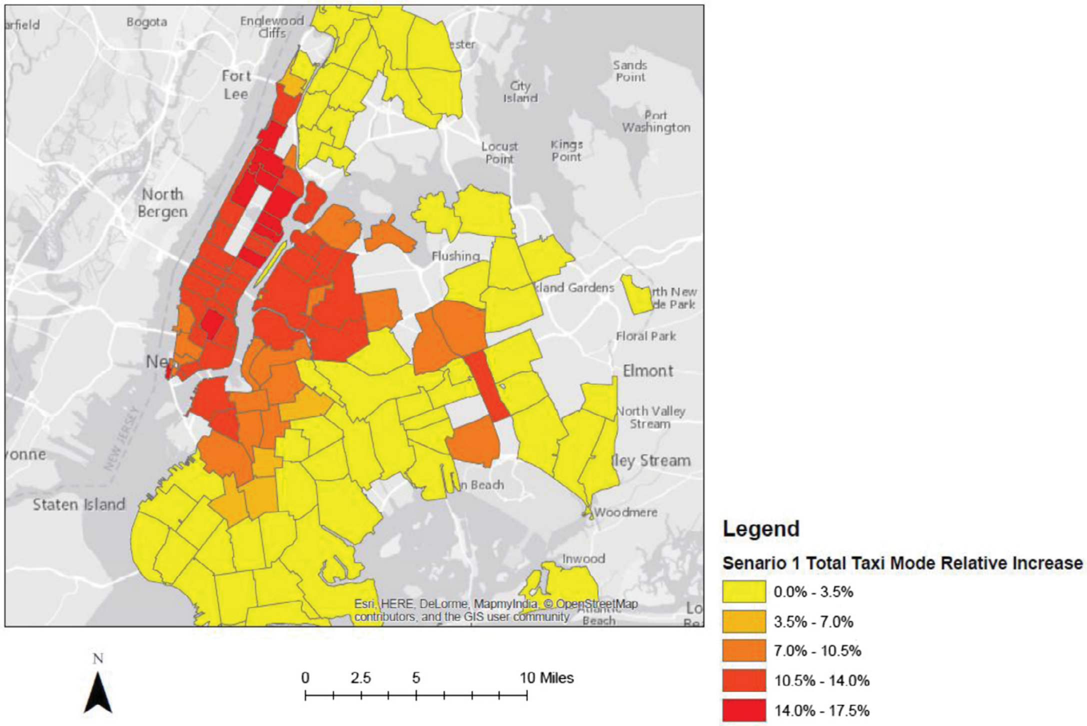
In this structure, the higher of the two utilities is assumed to determine the conditional preferred alternative between solo taxi and shared taxi. The trade-off arises if cost of waiting or detour is too high due to low density and/or low preference

Table 3
Validation of estimated model on baseline data.

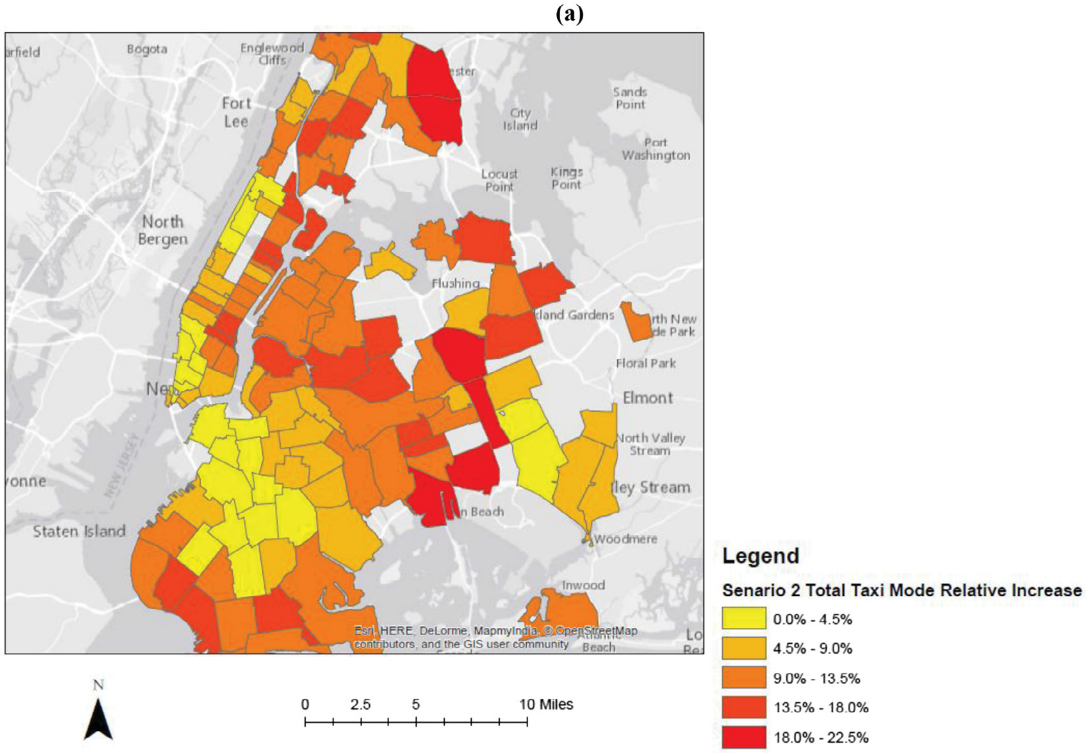
Mode	Observed share	Estimated share	Difference
Taxi/FHV	60.5%	64.7%	+4.2%
Transit	25.1%	23.5%	−1.6%
Other	14.5%	11.9%	−2.6%

Table 4
Summary of shared taxi scenario impact on mode share.

Alternative	Baseline model	Wait-share policy	Difference from baseline	Space-share policy	Difference from baseline
Taxi (shared and solo)	64.7%	70.4%	+5.7%	70.0%	+5.3%
Solo taxi	64.7%	16.8%	−47.9%	3.5%	−61.2%
Shared taxi	0%	53.6%	+53.6%	66.5%	+66.5%
Transit	23.5%	19.8%	−3.7%	19.9%	−3.6%
Other	11.9%	9.8%	−2.1%	10.1%	−1.8%



(a)



(b)

Fig. 5. Spatial distribution of relative increases in taxi mode in study area due to (a) wait-share policy, and (b) space-share policy.

for shared ride. The use of only the observable representative utility in determining the conditional split between solo and shared taxi is justified because we're not using the model to predict a new person's choice and the changes to the current individuals are only from observable variables.

Handling the endogenous variable for the wait-share policy

In the wait-share policy, the variable f_n' is a function of p_s, which is a measure of total percent of individuals who would choose shared ride given that they choose taxi. Since that is endogenous, we need to use an iterative update of the choice probabilities in the wait-share policy scenario to determine the expected wait time and resulting conditional choice between the two alternatives. We propose an iterative update in Algorithm 1 to obtain a fixed point for p_s.

Algorithm 1: iterative update to address endogenous mode share in wait-share policy

1. Assume an initial $\hat{p}_s = 0.50$.
2. Update f_n' based on $\hat{p}_s$, then determine from Eq. (9) whether each individual would conditionally choose shared taxi or single passenger taxi. Let the percent of individuals choosing shared taxi be p_s.
3. If $\hat{p}_s \neq p_s$, let $\hat{p}_s = p_s$ and go to 2, else stop.

The algorithm converges to a fixed point after 5 iterations a tolerance of 10^{-10}. We find that $p_s = 76.2\%$ of the 906 sample population would prefer to use shared taxi if the wait-share policy was an available option.

Results and discussion

The mode choices are computed for the three alternatives: (a) taxi with option available for shared ride, (b) transit, and (c) other. A summary of the changes from the baseline model is shown in Table 4.

By having the option to serve passengers as a shared ride, taxis and FHVs on average across the city would gain 4–5% market share to access JFK airport. The space-share policy leads to a higher preference from users to adopt shared ride over solo ride. However, a majority of the taxi ridership gain is taken at the expense of transit ridership.

A spatial distribution of the average relative increase *(new mode share – old mode share)/(old mode share)* in taxi mode choice per person as a result of the two shared taxi policies is shown in Fig. 5. The map reveals some very interesting insights. In Fig. 5a, the yellow zones have lowest changes in taxi market share, likely because of either insufficient density to have adequate wait time. On the other hand, Fig. 5b shows that many of the lower density areas benefit in taxi ridership increase when operating space-share policy.

We also take a look at the welfare measure and elasticities, as shown in Table 5. These values show that shared taxi operations would increase consumer surplus of JFK airport access travelers by 11–13%, with the wait-share policy slightly better off than the space-share policy. This is an interesting result, as the Fig. 5b suggests more of an average taxi share increase due to the policy. However, the increases are mostly in areas with low demand density, resulting in a net improvement that is less than the wait-share policy.

Introducing shared taxi operation also reduces the average elasticity to cost by 15–18%, which suggests passengers under the shared taxi operations would be less sensitive to fare costs. This makes sense, as the costs are divided between multiple passengers.

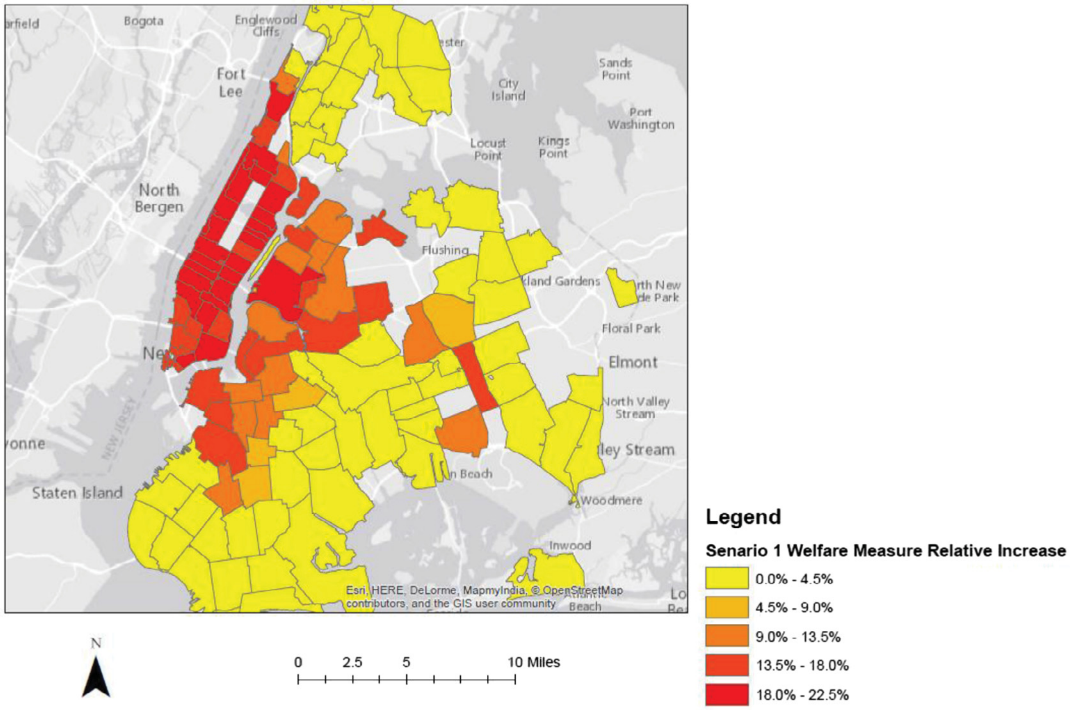
The total spatial welfare effects of the two shared taxi policies on the 906 sample are presented in Fig. 6. The two maps share some aspects in common: many of the zip codes generally will not benefit from a shared ride policy. Only a cluster of regions significantly benefit from the policies. The cluster differs between the two policies. In the wait-share policy, the benefits are more magnified, but concentrated around Manhattan. This makes sense because passengers have the most to gain in high density zones with short wait times for other passengers in the same zone. In the space-share policy, the benefits are more spatially distributed further out into Queens and parts of the Bronx.

To summarize the findings:

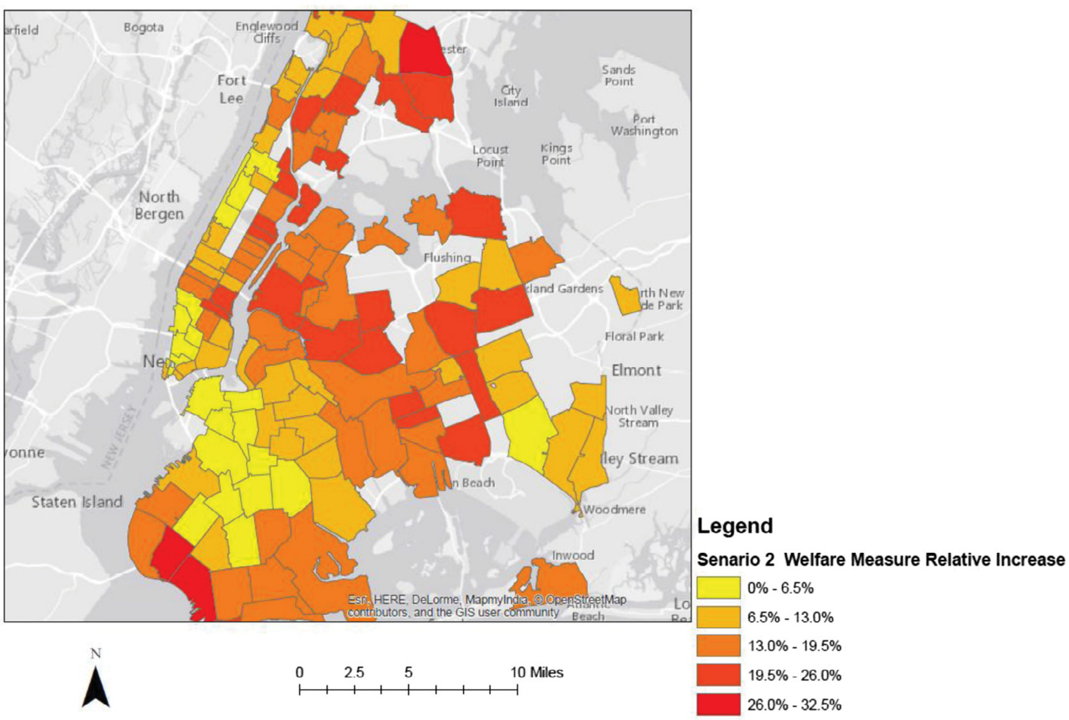
- A model estimated of the airport access mode choice suggests the elasticity of taxi demand with respect to the travel cost is similar in magnitude to the public transit elasticity.
- Applying either of the two proposed shared taxi policies would only increase taxi ridership by approximately 5 percentage points, and most of that would come from cannibalizing public transit ridership.
- The gains in taxi ridership are drastically different between the wait-share and space-share policies. For the wait-share policy, the average gains are lower, but highly concentrated in dense portions of Manhattan. For the space-share policy, average gains per passenger are high but these gains are made in mostly less dense areas.
- Welfare gains are significant, at the 11–14% level for the two policies relative to solo taxi service. The spatial allocation of these gains differ greatly between the two policies, with most of the gains in the wait-share policy made in Manhattan and the gains in the space-share policy spread out more.

Table 5
Summary of shared taxi scenario impact on welfare measure and elasticities.

Measure	Baseline	Wait-share (% diff.)	Space-share (% diff.)
Average consumer surplus	1.43	1.63 (+13.5%)	1.60 (+11.7%)
Average elasticity to cost	−0.27	−0.22 (−17.4%)	−0.23 (−15.5%)



(a)



(b)

Fig. 6. Spatial distribution of relative changes of total consumer surplus due to (a) wait-share policy, and (b) space-share policy.

- In the context of the spectrum of shared taxi policies, any of the current sharing services that have some combination of waiting with limits and spatial matching with limits (e.g. Lyft) are expected to be increasing consumer surplus (possibly in the 10% range), increasing airport access demand by FHV by 5% (but mostly taking that away from public transit), and

Table 6
Sensitivity of mode split and consumer surplus difference in scenarios from (+10%,−10%) in variables.

Scenario	Sensitivity Change	% Taxi	Shared Ridership	Consumer Surplus
Base Case	Original	64.65%	0	1297.64
Wait-Share Policy	Original	70.39%	486	1473.06
	Value of time increase 10%	70.34%	485 (−0.07%)	1471.55 (−0.10%)
	Value of time decrease 10%	70.45%	487 (+0.22%)	1474.60 (+0.10%)
	Wait time premium increase 10%	70.34%	485 (−0.23%)	1471.36 (−0.12%)
	Wait time premium decrease 10%	70.44%	487 (+0.21%)	1474.46 (+0.10%)
Space-Share Policy	Original	69.99%	603	1449.83
	Value of time increase 10%	69.80%	584 (−3.06%)	1443.97 (−0.40%)
	Value of time decrease 10%	70.19%	613 (+1.69%)	1456.02 (+0.43%)

much of the benefits are likely going to passengers from Manhattan. If policy-makers are interested in catering to passengers in the other boroughs more, they can consider regulations to incentivize operators to shift their policy more towards a space-share policy.

Sensitivity analysis

Two of the parameters in this study were assumed from prior studies: the value of time ($101.4/hr) and the wait time premium (1.76). To ensure that the findings of the study do not depend heavily on these values, we conduct a series of sensitivity tests.

The value of time impacts both the wait-share policy and the space-share policy. The wait time premium only impacts the wait-share policy. For each parameter, we increase and decrease the parameter by 10% to evaluate the effect of such a change on the share of taxi mode among access modes, shared taxi ridership, and the relative welfare measure.

The results of the sensitivity tests are reported in Table 6. The rows that show "Original" sensitivity change refer to the original parameter assumptions. For the shared ridership and welfare measure, the percent change from the original parameter scenario is shown for each test in parenthesis.

We can see that the welfare measure is quite insensitive to these two parameters, regardless of operating policy. The highest change is still less than 0.50% change resulting from a 10% change in the parameter. The taxi mode share and shared taxi ridership are also quite insensitive to the parameter changes. The biggest shift is with the space-share policy, where a 10% increase in value of time leads to a 3% decrease in shared taxi ridership from the original value. These results affirm the stability of our findings based on the assumed parameter values.

Conclusion

In this study, we set out to quantify the demand for shared taxis to access JFK airport, given the lack of such studies in the literature. Our approach is a mix of empirical and methodological. We develop a methodological framework around two extremes for evaluating shared taxi policies in either wait-share or space policies. Using a data set of 4023 samples from PANYNJ, we estimate a good fitting mode choice model with significant parameters to establish a baseline. From this baseline we are able to compare welfare measures, elasticities, and individual preferences for taxi, transit, and other paid options.

The method of evaluating the shared taxi policies is to treat the taxi choices within a single alternative based on the maximum of the single passenger and shared ride utility functions. This works because we are doing a direct comparison of policies on the same individuals that we estimated functions for, and are only changing the observable variables in the new scenarios. The wait-share scenario requires estimating the expected wait times as a function of the percent choosing shared taxi over solo taxi, which is performed by a fixed point algorithm. The space-share scenario is evaluated by constructing a sorted zone set by distance from the airport, and computing an expected fare based on change in travel cost and dividing fare costs by proportion.

Several insights are made from this research, which should benefit policymakers and taxi operators alike. The findings suggest that having the option for shared taxis benefit passengers in NYC going to JFK airport by 11–14% increase in consumer surplus. However, the increase in taxi ridership will generally come at a cost to transit ridership. Furthermore, the population in NYC benefitting most is highly dependent on the shared taxi policy. A wait-share policy benefits passengers from the dense parts of Manhattan most, while the space-share policy distributes the benefits more spatially to other boroughs.

This research should benefit not only the airport access literature, but it should also benefit other last mile research efforts. The findings complement the work in developing technologies for airport taxi dispatch systems (Yazici et al., 2016). The work can be further refined by shared mobility operators to locate geographical areas to match shared rides to the airport.

Future research should consider evaluating more sophisticated matching and fare allocation policies so that guidelines can be established for last mile planning. More advanced models can also be considered, such as the use of latent variables demonstrated by Al-Ayyash et al. (2016) in one of the only other shared taxi demand studies. Optimal switching methods based on using the demand model with real time demand data can be explored to maximize the value under different scenarios under uncertainty. While this study examines the demand for taxis to take to the airport, we have so far ignored the impact on the supply side. As mentioned in the literature review, several studies (e.g. Yang and Wong, 1998; Yang et al., 2010; Yang and Yang, 2011) have looked at taxi market equilibrium models which would be needed here. More recent efforts by Zha et al. (2016) and He and Shen (2015) tackle e-hailing and ride-sourcing services. In other parallel efforts we have also been studying equilibrium models based on day-to-day adjustment processes (Djavadian and Chow, 2017a,b) and also from dynamic equilibrium models (Correa et al., working paper). Further research in this direction would help illuminate the impact of taxi sharing on both the supply and demand sides of the market.

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