Value of convenience for taxi trips in New York City

Mehmet Baran Ulak a,*, Anil Yazici b, Mohammad Aljarrah c

a Department of Civil Engineering, University of Twente, Enschede 7522 NB, Netherlands
b Department of Civil Engineering, Stony Brook University, Stony Brook, NY 11794, United States
c Department of Civil Engineering, Texas A&M University, College Station, TX 77843, United States

ARTICLE INFO
Keywords:
Taxi trips
Value of convenience
Value of time
Multilevel modeling
Variation of value of convenience

ABSTRACT
The alternative public transportation options such as subway, bus, or taxi compete with each other to attract passengers. The competition depends on many factors such as travel time, reliability and convenience. Convenience is a collection of attributes affecting the attractiveness of the service including access and egress easiness, service frequency, crowding, comfort and information availability. It can be argued that the taxi preference when there is viable public transportation option is associated with the perceived convenience of taxis. The objective of this study is to evaluate the value associated with convenience of taxis in New York City by utilizing the large taxi trip data. First, the taxi trips which could be replaced by subway without any access or service availability issues (e.g., no transfers between subway lines) are extracted. Then, a multilevel modeling approach was utilized to estimate the monetary value associated with taxi convenience were estimated for different day-of-week and time-of-day periods, and areas in Manhattan. The results show that the value of convenience varies depending on the ratio of taxi travel time to subway travel time, and occasionally intersect when the ratio is close to 1. Furthermore, the corresponding value of convenience (VC) at those points (i.e., taxi travel time is equal to subway travel time) is close to $32/hr for all the zones during weekdays and weekends. Results also indicate that value of time is generally higher at peak hours during weekdays, whereas it is lower during weekend and social period at night and early morning hours.

1. Introduction

Alternative public transportation options such as subway, bus, or taxi compete with each other every day to attract passengers. The passengers choose among alternative options depending on their preference of travel time, reliability, cost, convenience or comfort, and so forth. Value of convenience is one of such factors which has substantial effect on the mode choice. Anderson et al. (2013) discuss convenience as covering all attributes which affect the attractiveness of the service including access and egress easiness, service frequency, crowding, comfort and information availability. Accordingly, transportation service convenience can be related to attributes including service availability, accessibility, frequency, crowding, comfortability, information availability, customer service, and security (Krygsman et al., 2004; Li et al., 2018; Litman, 2008; Trompet et al., 2013; Wardman, 2014). Besides the qualitative understanding of what constitutes convenience, there is also a need to quantify it in order to develop optimal pricing strategies for different travel modes.

It is generally difficult to quantify convenience (i.e., in monetary terms). In addition, the emergence of on-demand transportation
and micromobility modes complicates the evaluation of convenience. For instance, transportation network companies such as Uber and Lyft offer shared rides for their customers who trade the convenience of single occupancy ride and shorter travel time with reduced cost of ride but longer travel time. Companies such as Via offer further trade-off by asking the customers to walk to/from nearby locations along the taxi path to take the shared ride. Meanwhile, e-scooters as an emerging micromobility mode provides not necessarily as convenient as taxis, but inexpensive and fast travel option for short distances. E-scooter help alleviate the first-last-mile accessibility for transit modes, but it is also reported that e-scooters also replace transit for short distances (e.g., couple stops) (Portland Bureau of Transportation, 2018). Within this picture of emerging modes and services, it becomes even more challenging to pinpoint how travelers value convenience.

One way to estimate the value of convenience is mass passenger/customer surveys for multiple modes of transportation. Even ignoring the challenges brought about by multiple modes, such surveys are costly to prepare, distribute, and analyze. On the other hand, transportation engineers and planners have the opportunity to utilize growing number of actual trip datasets that are enabled by the mass utilization of GPS enabled devices. Taxi is one of the modes that large quantities of trip records are available for researchers. These big datasets reveal the temporal, spatial, and other factors (e.g., weather) that motivate a traveler to choose a taxi ride over another mode such as a viable transit option. For instance, more than 400 K trips per day are made by yellow cabs-only (i.e., not considering ride-hailing rides) in New York City (NYC), despite the extensive availability of public transportation options.

One of the main appeals of taxi service is that it provides door-to-door access as opposed to public transportation which serves only between designated stations. Moreover, taxis provide a secluded environment (as opposed to subway and bus), perceived as safer (e.g., during late night) and more comfortable (Anable and Gatersleben, 2005; Verplanken et al., 1994), and easier to access in most cases (e.g., during bad weather). In other words, taxis exhibit most of the features that are traditionally accepted to constitute a convenient transportation mode. However, this convenience comes with higher cost (i.e., taxi fare vs. subway fare). In addition, especially in the congested NYC road network, taxis are not necessarily the quickest way to travel. Therefore, shorter travel time is often not an advantage pertaining to the taxis, yet the travelers can still choose taxi services despite the loss in travel time.

In this study, it is assumed that the taxi preference over a viable subway option is associated with the perceived convenience of taxis. Accordingly, the value associated with this convenience is evaluated using the trade-offs in travel time and trip cost with respect to the subway-equivalent taxi trips, i.e., originated and ended close to the subway stops (within 0.125 miles radius) with no intermediate transfer. For this purpose, NYC Taxi and Limousine Commission (TLC)’s taxi trips dataset was obtained from the database of the City of New York (NYC, 2020a) and studied considering the day of week, time of day as well as the zones in Manhattan (i.e., at or out of central business district). The results reveal the trade-off between travel time and (in)convenience that can be inform policy makers and planners regarding the value of convenience in general, and optimal pricing of shared-ride transportation options in particular.

2. Literature review: definition of convenience and ways to estimate the value of convenience

For over four decades, the factors that lead to user preference for transportation options have been an important topic. A pioneering survey-based study was conducted by Middendorf et al. (1975) in order to compare bus trips and shared-ride taxi trips at two small urban regions, namely Davenport, Iowa, and Hicksville, New York. Primarily, taxis are found to be preferred by users as they are more flexible than other public transportation options (e.g., bus, subway) in terms of the pick-up and drop-off locations (Li et al., 2017). This flexibility brings about an advantage to taxis that can be described as part of the convenience. The effect of convenience can also be identified by investigating the taxi trips which increase around social attractions such as restaurants at late evening hours (Kim, 2018).

It is clear that comfort and convenience are factors predisposing individuals to prefer private cars (including taxis) over mass transit options such as buses or subways (Anderson et al., 2013; Litman, 2008). The lack of convenience is considered as the fourth most prominent disadvantage of public transit according to (Huey and Everett, 1996). Convenience is often used interchangeably with other travel aspects such as reliability and comfort (Crockett and Hounsell, 2005), and can affect all steps of a trip from planning to arrival to the destination. Several convenience related factors such as crowding, comfort, and safety can affect mode preference of passengers. Crowding can be harmful to riders’ health (e.g., stress issues and anxiety), cause safety issues and personal space intrusion, and reduced productivity. In addition, crowding is found to increase travel time cost and marginal disutility (Batarse et al., 2016; Haywood et al., 2017), and can translate into delays in the system (Cox et al., 2006; Tirachini et al., 2013).

Other factors which can be linked to convenience are the value of travel time and travel time reliability (Carrion and Levinson, 2012; Fosgerau and Engelson, 2011; Lam and Small, 2001; Li et al., 2014; Nam et al., 2005; Senna, 1994; Small, 2012). For instance, Yao et al. (2014) argue that travel time reliability/uncertainty must be incorporated into transit network design, because an unreliable system lead to inconvenience, and hence may compel transit users to use other alternatives. For instance, overcrowded subway cars of NYC subway prevent passengers from boarding during rush hours, increase the waiting and travel time as well as the travel time variability. This can affect passengers’ perceived convenience level and eventually might drive subway riders to consider alternatives.

The perception of convenience also depends such as travelers’ income, purpose of travel, and travelling distance and time (Li and Hensher, 2011; Whelan and Crockett, 2008). Studies show that cost of travel time tends to increase for uncomfortable and unsafe trips; is higher for high income individuals and lower for children and retirees; might be “negative” for enjoyable or social trips (e.g., recreational); and increases with uncertainty and unreliability (Litman, 2008).

Despite the important influence of “convenience” on the user’s mode choices, it is very difficult to quantify the value of convenience. An approach to measure the value of convenience is to convert convenience into equivalent amount of travel time which translates into variation in the demand. For example, with this approach, the effect of overcrowding (e.g., doubling the number of passengers from comfortable level) is equivalent to 3 times increase in the travel time, and hence to the effect of such travel time increase on the demand (Anderson et al., 2013).
Table 1
Analysis periods for day-of-week and time-of-day.

| Analysis Periods   | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday | Sunday |
|--------------------|--------|---------|-----------|----------|--------|----------|--------|
| 00:00 - 05:00      |        |         |           |          |        |          |        |
| 05:00 - 07:00      |        |         |           |          |        |          |        |
| 07:00 - 10:00      |        |         |           |          |        |          |        |
| 10:00 - 16:00      |        |         |           |          |        |          |        |
| 16:00 - 21:00      |        |         |           |          |        |          |        |
| 21:00 - 00:00      |        |         |           |          |        |          |        |

Legend: **Weekday**  **Social**  **Weekend**

**Fig. 1.** Study area and selected taxi trips.
Descriptive statistics of taxi trips used in the analyses.

|                  | Travel Time (min) | Travel Distance (mi) | Fare ($) | Occupancy |
|------------------|-------------------|----------------------|----------|-----------|
| **CBD # : 240,261** |                   |                      |          |           |
| Mean             | 8.86              | 1.26                 | 9.0      | 1.65      |
| Median           | 7.18              | 0.99                 | 7.8      | 1         |
| Std. Dev.        | 6.32              | 0.85                 | 4.1      | 1.31      |
| 5th %ile         | 2.18              | 0.38                 | 4.8      | 1         |
| 95th %ile        | 21.28             | 3.11                 | 17.4     | 5         |
| **Non-CBD # : 73,345** |                  |                      |          |           |
| Mean             | 5.87              | 1.10                 | 7.6      | 1.65      |
| Median           | 4.87              | 0.87                 | 6.8      | 1         |
| Std. Dev.        | 3.94              | 0.82                 | 3.1      | 1.32      |
| 5th %ile         | 1.78              | 0.38                 | 4.8      | 1         |
| 95th %ile        | 13.27             | 2.57                 | 13.1     | 5         |

Another concept used to quantify the convenience is called “willingness-to-pay” for a better service. For instance, Eboli and Mazzulla (2008) conducted a survey-based study to identify willingness-to-pay for service quality and reliability of bus system through university students. Authors found that students are willing-to-pay for comfort and convenience (e.g., cleanliness, less crowding) more than half of what they would pay for reliability. A recent study by Li et al. (2018) investigates the value of convenience offered by taxis by formulating a mode choice model based on surveys in Beijing, China. However, such surveys are difficult to conduct and do not readily exist for most cities, including New York City.

The convenience of taxis is often associated with non-shared rides that provide comfort and door-to-door service without the compromise from travel time, i.e. no intermediate stops. Nonetheless, shared-ride taxi services had been considered as a viable public transportation option in the past (Englisher, 1984; Teal et al., 1980). Studies of Teal et al. (1980) and Englisher (1984) presented findings on the effectiveness of shared-ride taxi systems as they become public transit providers contracted by local governments. However, these shared-ride taxi systems have not been utilized for a long time until recently, i.e., when the ride-hailing companies such as Uber and Lyft started to offer shared-ride options. Englisher (1984) argued that shared-ride taxis were deemed less convenient by some users (e.g., very long wait times, safety, etc.). This may lead officials to abandon this system as a public transportation option. However, the emergence of mobile devices with GPS capabilities provides some of the necessary data input to overcome the inefficiencies of traditional shared-ride systems (e.g., demand uncertainty and online route planning to minimize travel times).

The share of taxis in the “non-shared ride” market has been continuously reducing in the last eight years (Paraboschi et al., 2015). This decline is partly due to the ride-hailing companies who take advantage of the mobile technologies and offer ridesharing option to their users to reduce the individual trip cost while increasing the travel time – thus reducing the convenience. In other words, ride-hailing services showed that ridesharing is a viable option for passenger who are willing to pay less by trading off their convenience. Paraboschi et al. (2015) showed that adoption of ridesharing in traditional taxi industry will help them to compete with ride-hailing companies. Similarly, Al-Ayyash et al. (2016) showed that a shared-ride taxi service can attract new customers due to lower trip costs. However, utilization of such shared-ride taxis depends significantly on the fare difference, which relates to the trade-off between the travel time (hence value of time) and convenience. However, the literature on optimal pricing of the shared-ride trips are scarce.

Currently, the ride-hailing companies use the advantage of monitoring demand in real time, establish varying demand-responsive prices (e.g. surge pricing) that maximize profit rather than utilization. Traditional taxi services do not have similar real-time demand monitoring, hence require more static pricing rules for shared rides. Considering the congestion impacts of empty or customer-searching taxis at cities (Schaller, 2017), it is important to understand the trade-off between travel time and convenience to implement ridesharing that can increase the taxi utilization. This study can help calibrating such pricing efforts by identifying the value associated with convenience and time as well as the ratio of these variables.

### 3. Study area and data

The study was conducted by using NYC Taxi and Limousine Commission (TLC)’s taxi trips dataset for February 2016 in Manhattan, New York City. The trips were categorized based on the day of week (weekday, weekend, and social) and time of day (“00:00–05:00”, “05:00–07:00”, “07:00–10:00”, “10:00–16:00”, “16:00–21:00”, and “21:00–00:00”). Note that, weekdays correspond to the working days of the week, whereas social period is the time of week when taxi usage increase as social activities increase such as Friday evening (Table 1). The remaining time periods were classified as weekend periods.

Due to the lack of detailed traffic congestion and trip purpose data, the taxi trips were categorized as Central Business District – CBD (South of 59th street) and Non-CBD (North of 59th Street) trips, following the designation in New York City Congestion Pricing plan (State of New York, 2019). Fig. 1 shows the coverage of CBD and Non-CBD, along with the studied subway lines. Accordingly, the taxi trips whose origin and destination are located either in CBD or in Non-CBD were extracted (i.e., both origin and destination of a taxi trip has to be either in CBD or in Non-CBD).

The dataset was cleaned for erroneous records, e.g., trips with 0 min travel time or miles distance travelled, fare less than $2.5 (initial charge for taxis in NYC), trips originating and arriving at the same place, and trips with average speed less than 2mph. Then, these taxi trips were “matched” with equivalent subway trips. For the analysis, the taxi trips originated and ended around the stops of subway lines 1, 4-5-6, 7, A-C, E, and L were used. For this purpose, taxi trips originating and ending within 200 m of a subway stop (corresponding to about 1 avenue and 2 streets block, and 2-4 min of walking time) were identified (Fig. 1). In order to avoid the
impacts of transfer time between the subway lines along the subway trip, only the taxi trips that have the origin and destination on the same line were extracted. These taxi trips were assumed be equivalent because the corresponding subway trips eliminate the door-to-door advantage of taxi trips due to the closeness of the subway stop. Note that, it was assumed that taxi and subway are the only available modes of travel, i.e., walking or bus alternatives were neglected. Moreover, the yellow cabs in NYC are strictly street hire due to the relevant law.

A total of 389,644 taxi trips (240,617 trips within the CBD while 73,429 trips within the Non-CBD) were classified into 28 analysis groups composed of two zones (CBD and Non-CBD), three day periods (weekday, social, weekend), and six time-of-day periods (please see Table 1). The taxi trip dataset contains information such as pick-up and drop-off timestamps which were used to calculate trip duration and the time of the trip. The dataset also includes total trip fare and number of passengers in each trip. In the dataset, 1, 2, 3, 4, 5, and 6 occupancy taxi trips correspond to 72%, 14%, 4%, 2%, 5%, and 3% of total trips (389,644), respectively. Please see Table 2 for the descriptive statistics of the resultant taxi trip dataset.

Note that the analysis conducted based on total taxi fare rather than fare per passenger because the number of passengers is entered by the taxi drivers who are not obliged to record this information accurately; hence the data are not reliable. Consequently, taxi occupancy was assumed to be one (which is not far from general characteristics of taxi utilization in NYC); thus, no fare-split options were considered. Nonetheless, an additional analysis based on the fare per passenger is also conducted and presented in the Appendix B. Subway trip cost, on the other hand, is fixed for $2.75 per ride regardless of the distance. Nevertheless, a sensitivity analysis was also performed to take the subway pass holders into account.

The travel time of equivalent subway trips and average waiting time for subway travel were calculated based on MTA schedules. Average waiting times were calculated based on half of the scheduled train headways. Different time frames were assigned different subway waiting time as follows: "00:00–05:00": 10 min, "05:00–07:00": 4 min, "07:00–10:00": 2.5 min, "10:00–16:00": 2.5 min,"16:00–21:00": 2.5 min, and "21:00–00:00": 5 min. The potential additional subway waiting time due to skipping an overcrowded train was not taken into account. In addition, subway access/exit times were calculated using the actual data (i.e., distance of pick up and drop off locations from respective subway stations) and added to the total subway travel time.

4. Analysis of taxi trips: travel times, fares, and equivalent subway trips

4.1. Temporal trends in subway-equivalent taxi trip frequency

Fig. 2 shows the temporal trends in the frequency of subway-taxi equivalent trips. There are total of six figures (two zones and three-day periods) that illustrate the frequency of taxi trips for different times of day and travel time. There is a consistent trend that the highest number of subway-equivalent taxi trips is always around 7:00–8:00 PM during weekdays and social period; whereas it is between 12:00–16:00 PM during weekends. Please note that the “weekend” period does not cover Saturday evening (after 4:00 PM).
since the evening time is covered by “social” period (please see Table 1). Therefore, the high frequency bins are shifted towards midday (12:00–16:00 PM) in the “weekend” period. Fig. 2b and c also show that there are considerable number of subway-equivalent taxi trips before and after midnight during “social” period. Another interesting result is that majority of the taxi trips are shorter than 15 min in both zones and all-day periods. The taxi fare starts with $2.5 (flag drop fare) plus surcharges, making taxi trip an expensive option for short distances. Nevertheless, the passengers still utilize taxis for short trips. These short but expensive trips have potential to provide insights about value of convenience. However, it is necessary to compare the taxi travel times with the equivalent subway trip times. This is investigated in the next section.

4.2. Comparison of taxi trips with equivalent subway trips

Similar to the 2-D temporal trend histograms, Fig. 3 illustrates the comparison of taxi trip times with equivalent subway trip times. As Table 3 shows, the percentage of trips which taxi travel time is shorter than equivalent subway travel time varies depending on the zone, day-of-week, and time-of-day. Note that, 60% of all taxi trips take less time than the subway trips, whereas 40% of trips would be shorter with an equivalent subway trip. Taxi trips appear to have more favorable travel times during social period. This is especially visible after midnight when the subway headway (hence waiting time) is longer, e.g., a secondary group of bins that are visible above 10 min subway travel time in Fig. 3b and e. Moreover, Fig. 2b and e (2-D histograms of taxi trips) shows that there are considerable number of taxi trips before and after midnight during “social” period.

In summary, taxi seems to be more advantageous than subway in terms of travel time, particularly at “social” period. Fig. 3 also shows that subway might be advantageous for trips longer than 10 min. In the next section, we investigated the travel time and cost

![Fig. 3. 2-D Histogram of taxi travel time vs. equivalent subway travel time.](image)

### Table 3

The percentage of trips which taxi travel time is shorter than equivalent subway travel time.

|        | CBD       |         |         | Non-CBD   |         |         |
|--------|-----------|---------|---------|-----------|---------|---------|
|        | Weekday % | Social %| Weekend %| Weekday % | Social %| Weekend %|
| 00:00–05:00 | 99       | 98      | –       | 99        | 99      | –       |
| 05:00–07:00 | 93       | –       | 94      | 96        | –       | 97      |
| 07:00–10:00 | 34       | –       | 71      | 58        | –       | 86      |
| 10:00–16:00 | 24       | –       | 39      | 54        | –       | 70      |
| 16:00–21:00 | 33       | 26      | 37      | 62        | 62      | 71      |
| 21:00–00:00 | 81       | 58      | 84      | 96        | 95      | 97      |
differences between taxi and equivalent subway trips in order to identify why some passengers are willing to pay more to taxis.

4.3. Travel time difference vs. fare difference

The relationship between travel time difference (Taxi Time – Subway Time) and fare difference (Taxi Fare – Subway Fare) were calculated in order to investigate why some passengers are willing to pay more to taxis. In Fig. 4, six plots (one plot for each time frame, e.g., 00:00–05:00) illustrate this relationship for all days and for whole Manhattan. It is clear that taxis have travel time advantage during night (00:00–05:00). Taxis are slightly advantageous during late evening (21:00–00:00) and early morning (05:00–07:00). The taxis mostly lost their travel time advantage during the day and peak hours.

One can observe that the plots are shifting towards right (where equivalent subway trips are shorter) starting from early morning until the late evening. Since these trips are equivalent trips, one can argue that taxi passengers were willing to pay for the convenience provided by taxis, and the potential reduction in travel time. The relationship between the fare difference and travel time difference is used to estimate the value associated with the convenience and time. The next section provides findings of this analysis.

5. Modeling the relationship between value of time and convenience

We hypothesized that the cost difference between a selected taxi trips and an equivalent subway trip stem from two main factors: 1) convenience provided by taxis, and 2) potential reduction in travel time. It is a fact that taxis are not always faster than the subway (Table 3); hence taxi users are occasionally sacrificing from their time for more convenience provided by taxis. Table 3 shows the percentage of trips that the taxi travel time is shorter than travel time of an equivalent subway trip. The data shows that taxis are slower than subway during the working and commuting hours at CBD. Therefore, there are two cases for each taxi trip:

1. Taxi travel time is shorter than subway travel time: It is assumed that the cost difference is due to convenience and travel time savings by taxi;
2. Taxi travel time is longer than subway travel time: It is assumed that the taxi passenger not only paid more for convenience, but also lost time since taxi was slower (relating to value of time).

We modeled this relationship as follows:
ΔFar_{i,pz} = VC_{pz} \cdot (TT_{i,pz} - VT_{pz} \cdot ST_{i,pz} - TT_{i,pz})

where ΔFar_{i,pz} is the fare difference between taxi trip “i” at time period-zone pair “pz” (e.g., 07:00–10:00 – CBD) and an equivalent subway trip; VC_{pz} is the per minute dollar value associated with the convenience of taxis for time period-zone pair “pz”; TT_{i,pz} is the taxi travel time of trip “i” at time period-zone pair “pz”; VT_{pz} is the per minute dollar value of time for time period-zone pair “pz”; and ST_{i,pz} is the subway travel time of an equivalent subway trip for trip “i” at time period-zone pair “pz” (henceforth pz superscript is not shown in equations for the sake of simplicity).

This model implies that a passenger pays a certain amount ($ per minute) to have “taxi convenience”. For instance, when subway and taxi take the same amount of time, the fare difference can be attributed as the value associated with convenience. However, the convenience value of a taxi trip that takes twice longer than an equivalent subway trip is not equal to the case of ST = TT. In other words, when taxi takes more time (and costs more) compared to an equivalent subway trip, then the value of convenience may change, as the convenience does not necessarily increase when passenger spends more time in the taxi. A tangible example is how inconvenient a taxi trip can become under congestion, although the initial consideration for taxi choice had been the convenience. Therefore, we tested alternative mathematical models for the relationship between convenience and travel time, as presented in the following Table 4.

### Table 4
Alternative VC models.

| VC Model     | Function                                      | VC Model     | Function                                      |
|--------------|-----------------------------------------------|--------------|-----------------------------------------------|
| Linear       | \( VC = \alpha + \gamma \cdot \left( \frac{TT}{ST} - 1 \right) \) | Exponential - Negative | \( VC = \alpha + \gamma \cdot e^{\left( \frac{TT}{ST} - 1 \right)} \) |
| Quadratic    | \( VC = \alpha + \gamma \cdot \left( \frac{TT}{ST} - 1 \right)^2 \) | Exponential - Positive  | \( VC = \alpha + \gamma \cdot e^{\left( \frac{TT}{ST} - 1 \right)} \) |

Fig. 5. AIC difference between the “Exponential-Negative” VC model and the alternatives. The smaller the AIC, the better the fit of the model.
section.

5.1. Alternative functions for VC

The VC functions in Table 4 formulate the value associated with convenience with respect to the ratio of the taxi and subway travel times (i.e., TT/ST). The common characteristic of the tested models is that the value of convenience varies depending on the ratio of taxi travel time over equivalent subway travel time.

When developing VC functions, a constant term to represent the fixed price paid for value of convenience was not utilized in the formulation, because, a taxicab ride in New York City already involves a fixed cost (i.e., “flag down” fare) more than $3.3 plus time-of-day surcharges (NYC, 2020b). In other words, the taxi passengers are already aware that they pay a constant fare that is irrelevant of the travel time. Therefore, a constant term would not improve the explanation power of the model, although such approach might be mathematically feasible.

Each model was tested for significance, and the best fit among the significant models was selected by using Akaike’s Information Criterion (AIC) (Burnham and Anderson, 2002). The AIC values indicate the fitness of the model, and the lower the value of AIC, the better the fitness of the model. Accordingly, AIC can provide the relative superiority of the selected models with respect to prediction performance. Fig. 5 shows the AIC values of the tested models. AIC scores shows that the “Exponential-Negative” is the best model, i.e., the AIC of other models is almost always higher than the AIC of “Exponential-Negative” model (Fig. 5).

Note that, full models (i.e., Eq. (1) with the VC function plugged in) were needed to be built in order to test the goodness of fit of the alternative VC functions (i.e., AIC values of full models). Therefore, four alternative full models were developed (using functions in Table 4) and regression analyses conducted to estimates AIC values. As a result, the best fitting VC function (“Exponential-Negative”) was selected and the model built using with this alternative became the final model. Therefore, the final model (i.e., Eq. (3) presented in the following section) was actually built before calculating AIC values; however, the AIC values in Fig. 5 presented before Eq. (3) for the sake of clarity.

5.2. Final value of time and convenience model

Eq. (2) shows the initial fare difference equation (Eq. (1)) after “Exponential-Negative” model for the VC is substituted into Eq. (1). Eq. (2) can be further simplified by dividing both sides by the taxi travel time (Eq. (3)):

\[
\Delta \text{Fare}_c = \left( \alpha + \gamma^r e^{-\left( \frac{\gamma^r}{\gamma^v} \right) \left( \frac{\gamma^v}{\gamma^s} - 1 \right)} \right) \cdot \text{TT}_s + \text{VT} \cdot (\text{ST}_s - \text{TT}_s)
\]

\[
\frac{\Delta \text{Fare}_c}{\text{TT}_s} = \left( \alpha + \gamma^r e^{-\left( \frac{\gamma^r}{\gamma^v} \right) \left( \frac{\gamma^v}{\gamma^s} - 1 \right)} \right) + \text{VT} \cdot (\frac{\text{ST}_s}{\text{TT}_s} - 1)
\]

In order to estimate the coefficients \( \alpha, \gamma, \) and VT, we used multilevel modeling as taxi trips can be structured in different aggregate levels, i.e., origin-destination (O-D) pairs. Multilevel models are statistical approaches that are appropriate when the data represents events which may vary more than one level. In hierarchical multilevel models, observations are assumed to vary at more than one level and the observations are grouped at aggregate units at these levels. Detailed discussion on and application of hierarchical multilevel models can be found in (Gelman, 2006) and (Jones and Jorgensen, 2003). In this study, the taxi trips within the O-D pairs constitute the first level while different O-Ds form the second level. The second level can capture the aggregated group-wise variations between O-Ds. This approach can be extended to create more levels such as neighborhoods of Manhattan which can constitute the third level. A generic model consisting of two predictors with two-levels can be described as follows:

\[
Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + \beta_{2j} X_{ij}^2 + \epsilon_{ij}
\]

\[
\beta_{0j} = \gamma_{00} + u_{0j},
\]

\[
\beta_{1j} = \gamma_{10},
\]

\[
\beta_{2j} = \gamma_{20},
\]

\[
Y_{ij} = \gamma_{00} + \gamma_{10} X_{ij} + \gamma_{20} X_{ij}^2 + u_{0j} + \epsilon_{ij}
\]

where \( Y_{ij} \) is the response variable at first level, \( X_{ij} \) are first level fixed effect predictor variables, \( \beta_{0j} \) is the intercept of the response variable at second level, \( \beta_{1j} \) is the coefficient vector (slope) for the relationship between predictors and response in group \( j \), \( r_{ij} \) is the error term at the first level, \( \gamma_{00} \) is the overall intercept which is the mean of response variable across all groups, \( \gamma_{10} \) is the coefficient of the second level predictor, \( u_{0j} \) is the error term for the second level that corresponds to the deviation of group-wise intercepts from the overall intercept \( \gamma_{00} \). Moreover, \( \gamma_{10} \) is the regression coefficient set for the first level predictors while \( \gamma_{20} \) is the regression coefficient set for the second level predictors. Eq. (3) can be rewritten as follows in combined with the multilevel modeling form:
Given that:

\[ Y_{ij} = \Delta F_{Tij} \]

\[ X_{ij}^1 = e^{-\left(\xi_{ij} - 1\right)} \]

\[ X_{ij}^2 = \left(\xi_{ij}^{-1} - 1\right) \]

\[ \gamma_{00} = \alpha \]

\[ \gamma_{0i} = \gamma \]

\[ \gamma_{mi} = VT \]

Equation 3 becomes:

\[ \Delta F_{Tij} = \alpha + \gamma e^{-\left(\xi_{ij} - 1\right)} + VT \left(\xi_{ij}^{-1} - 1\right) + u_{0j} + r_{ij} \]

where \( \xi_{ij} = \frac{TT_{i1}}{ST_{ij}} \) and \( \Delta F_{Tij} = \frac{\Delta F_{arc_{i1}}}{TT_{i1}} \)

---

Table 5
Lognormally distributed Taxi Wait Time means and standard deviations.

| Time of Day     | mean (min) | Standard deviation (min) |
|-----------------|------------|--------------------------|
| 00:00–05:00     | 5.45       | 2.30                     |
| 05:00–07:00     | 2.70       | 1.15                     |
| 07:00–10:00     | 5.75       | 2.40                     |
| 10:00–16:00     | 2.70       | 1.15                     |
| 16:00–21:00     | 5.75       | 2.40                     |
| 21:00–00:00     | 2.70       | 1.15                     |

---

Fig. 6. Value of convenience (VC) functions at different time periods and zones. TT/ST: travel time ratio.
5.3. Sensitivity analysis and parameter estimation

To estimate parameters, we conducted a sensitivity analysis involving two factors that are assumed to be stochastic: 1) riders who own a monthly subway pass accounting for the zero marginal cost case (no cost of riding subway) for some taxi riders, and 2) taxi wait times that can vary based on time of day. To begin with, it is a fact that subway has zero marginal cost for monthly pass holders; however, it is not possible to identify which taxi riders may have monthly passes or what is the percentage of monthly pass holders among taxi riders. For example, according to an article published by The New York Times, a survey by the transportation authority indicates that the market share of monthly passes are 23% (Neuman, 2008). However, it is reasonable to expect that this share would be lower among the taxi riders. Therefore, it was assumed that the 0%, 5%, 10%, and 15% taxi riders have monthly passes. In the sensitivity analysis, taxi riders who have monthly passes were randomly selected based on the assumed percentages (0%, 5%, 10%, and 15%) and the subway cost is not accounted for in the “fare difference” for these trips.

We find literature very scarce in terms of taxi wait times. Nonetheless, Gandhi et al. (2011) states that taxi wait time is on average 5.59 min (Gandhi et al., 2011) in New York City, even though there is no information on the temporal variation of this wait time. Therefore, taxi wait times were stochastically assigned to each taxi trip using a lognormal distribution with means and variances depending on the time of day when trip was made (see Table 5). Note that, the means and variances of taxi wait times were assumed based on the findings of the Gandhi et al. (2011). As a result, 100 runs (i.e., Monte Carlo process) were completed and parameters such as mean and 95% confidence intervals were calculated for each model parameter.

In addition to the subway pass ownership and wait times, the number of passengers in a taxi can also impact the estimates. As discussed previously, the number of passengers in the dataset is not completely reliable, hence the taxi occupancy was assumed to be one. Nevertheless, a sensitivity analysis for multiple occupancy was also conducted, assuming that the data on occupancy is accurate. For this purpose, the formulation of the VC was modified by adding new parameter ($\zeta$) to represent the number of additional passengers to the first passenger ($P-1$), as below:

$$VC = \alpha + \gamma \cdot e^{(\frac{\mu}{\mu - 1})} + \zeta^k(P - 1)$$  \hspace{1cm} (6)

The results (which are presented under Appendix B for space considerations) show that the VC results for single occupancy were not...
affected considerably, and the model provided changes in VC as the taxi occupancy increases. The model can be re-estimated with reliable occupancy data to layout further implications.

6. The calculated values associated with convenience and time

The result of multilevel modeling of value associated with convenience and time are presented in Fig. 6 and Fig. 7 (please see Appendix A for estimates, and 95% confidence intervals of predictors - \( \alpha, \gamma \) and VT - utilized in regression models). Fig. 6 illustrates the variation in value of convenience (VC) with respect to the ratio of taxi travel time to equivalent subway travel time (i.e., TT/ST). Fig. 7, on the other hand, shows color labeled value of convenience and time (VT). It is intuitive to expect the VC to increase with increasing ratio of TT/ST; hence, the fare difference should be associated with the value of convenience. This consideration also implies that the passenger’s value of convenience is proportional to the time she/he spends in taxi, i.e., the value of convenience of a 20 min ride is double the convenience value of 10 min ride. However, this implication conflicts the observation that getting stuck in a taxi for a long period of time might be an inconvenient experience.

It can be observed that the variation in VC depends on the zone and day period. For instance, VC for “16:00–21:00” does not considerably change at the CBD on social; however it decreases significantly with increasing travel time ratio at Non-CBD on weekdays, social, and weekends. An intriguing finding is that the VC curves generally intersect when TT/ST is close to 1, except social period. This is a specific point where taxi travel time is equal to subway travel time; hence the effect of travel time on the fare difference is zero (please see Eq. (5)). Therefore, the fare difference only depends on the \( \alpha \) and \( \gamma \) which are parameters of the VC predicted by the multilevel model (please recall Eq. (2)). It is worth mentioning that these parameters are predicted using the complete dataset (for each period-zone pair, e.g., Weekday-CBD); hence, the parameter estimations do not reflect only the specific point where taxi and subway travel times are equal. Therefore, this intersecting pattern when the TT over ST ratio is close to 1 is not imposed by the assumptions associated with the functional form of VC and VT.

The corresponding VC at those points (i.e., TT = ST) is about $32/hr for all the zones during weekdays and weekends. Aligned with the literature, Fig. 7 also shows that VT is generally higher at peak hours (“07:00–10:00” and “16:00–21:00”) particularly during weekdays, and lower during weekend and social period at night and early morning hours (“00:00–05:00” and “05:00–07:00”).

On the one hand, it is a valid argument that the calculated monetary values associated with time and convenience would be valid only in NYC (albeit with reservations due to lack of individual preference data). On the other hand, taxi trip datasets are becoming increasingly available especially for major cities, and this paper provides the methodology to replicate the analysis for other cities. Moreover, if it is assumed that VT and VC will be similarly affected by socio-economic characteristics of the city residents (e.g., income), the ratio of VT and VC can still provide valuable information for other localities. For instance, VC fluctuates relatively less than VT, and fortunately VT values for different urban areas are far more available than VC. Hence, it can be argued that VC values can be calculated using the ratio of VT to VC and the local values of VT.

Specifically for NYC, the VC/VT ratio at CBD/social/12AM-5AM period is the highest, followed respectively by Non-CBD/weekend/5AM-7AM, Non-CBD/weekday/5AM-7AM, and Non-CBD/social/12AM-5AM. In other words, the travelers are more likely to pay higher fares for ridesharing during aforementioned periods and locations. That is, shared rides might be more attractive at time periods and locations with lower VT. Traditional taxi industry is heavily regulated with strict pricing rules and regulations. Hence, any ride-share pricing has to go through scrutiny and justification to be implemented. Given the severe competition with the ride-hailing companies and increase in the demand for cheaper shared-rides, setting the optimal ridesharing prices is crucial to maintain the industry. The methodology and the findings of this study can inform the decision makers how to implement potentially varying (with respect to time of day, day of week and location), yet optimal prices for ridesharing.

7. Conclusions

This study investigates the value associated with convenience (VC) of taxis. For this purpose, taxi trips (made in February 2016 in Manhattan, NYC) were compared with the subway-equivalent trips which could be replaced by subway without any access or service availability issues. Spatially, two zones were considered based on the NYC Congestion Pricing Plan: South of 59th Street as CBD and North of 59th Street as non-CBD. Temporally, three day-of-week periods were considered based on daily travel and taxis utilization patterns in NYC: weekday, weekend, and social (includes Friday and Saturday evenings and nights). For each day, six different time-of-day periods were considered: “00:00–05:00”, “05:00–07:00”, “07:00–10:00”, “10:00–16:00”, “16:00–21:00”, and “21:00–00:00”.

A multilevel modeling approach was utilized to estimate the value associated with convenience and time at these different zones, day-of-week and time-of-day periods. In order to reflect the inconvenience as the trip time gets longer, we modeled the value of convenience as a negative exponential function with respect to the ratio of taxi travel time to subway travel time. This was done considering that the convenience of a taxi trip would reduce as the travel time exceeds the equivalent subway trip time.

The results show that the VC curves occasionally intersect at a specific point when the ratio of taxi travel time over subway travel time is close to 1, which is intriguing. The corresponding VC at those points (i.e., TT = ST) is about $32/hr for all the zones during weekdays and weekends. Consistent with the literature, the results also indicate that value of time (VT) generally increases at peak hours during weekdays. Meanwhile, the VT decreases during weekend and social period at night and early morning hours.

7.1. Discussions, limitations, and future work

In general, the calculated monetary values are difficult to generalize to cities that do not have similar demographics and
transportation system to NYC. Nevertheless, the trade-off between the travel time and convenience, i.e., the VC/VT ratios, can inform the on-demand transportation providers, planners and policy makers. For instance, in a single-occupancy taxi trip (e.g., Uber, Lyft), the customer travels alone and directly goes to the destination. With introduction of shared trips (e.g., UberPool and Lyft Shared), the customers can choose to travel with other passengers and lose some time, but pay less money. On the one hand, Teal et al. (1980) and Englisher (1984) showed decades ago that traditional taxi services can offer such ridesharing options that can lead to a more efficient transportation system. However, their suggestions did not achieve traction in traditional taxi industry. On the other hand, ride-hailing companies showed that ridesharing is a viable option to satisfy transportation needs of individuals who are willing to pay less by trading off their convenience.

Literature shows that such ridesharing practices has potential to increase the competitiveness of taxi services; but identifying optimal fares is critical for the successful utilization of shared-ride transportation alternatives (Al-Ayyash et al., 2016; Paraboschi et al., 2015). However, literature lacks the quantification for the trade-off between time and convenience – a critical component to determine fares for ridesharing services. By utilizing a big transportation trip dataset, this study addressed this need to estimate the monetary value of convenience and provided comparisons with the value of time for different time-of-day and day-of-week periods (weekday-weekend, peak-off peak), and region (i.e., CBD vs. Non-CBD). The findings of our study provide insights on optimal pricing for ridesharing (especially for traditional taxi industry) by extracting when and where the travelers are more likely to pay for the trade-off between convenience and travel time.

It is worth mentioning that ideally the value of time studies employ surveys in which mode choice is explicitly stated. However, such survey data that can support discrete choice models and help develop a utility function are very rare, especially within the context of transit vs. taxi choice in metropolitan cities. As an alternative, a multilevel model structure is utilized in this study to estimate the value of convenience without costly data collection effort. However, the findings of this study can be supported by mode choice surveys that can be used to develop utility functions. In addition, investigation of alternative mathematical structures for VC can be a very promising future direction to further improve the proposed model.

**CRediT authorship contribution statement**

Mehmet Baran Ulak: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft. Anil Yazici: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing - original draft. Mohammad Aljarrah: Data curation, Investigation, Writing - original draft.

**Appendix A**

See Tables 6 and 7.

### Table 6

Parameter estimates for the CBD zone.

| CBD | Weekday | Social | Weekend |
|-----|---------|--------|---------|
|     | Time of Day | Est. | 95% CI | Est. | 95% CI | Est. | 95% CI |
| α  | 00:00-05:00 | 0.49 | 0.43–0.57 | 0.43 | 0.40–0.47 | 0.47 | 0.44–0.50 |
|    | 05:00-07:00 | 0.52 | 0.47–0.59 | – | – | 0.72 | 0.61–0.85 |
|    | 07:00-10:00 | 0.51 | 0.46–0.58 | – | – | 0.40 | 0.35–0.48 |
|    | 10:00-16:00 | 0.53 | 0.50–0.57 | – | – | 0.57 | 0.54–0.60 |
|    | 16:00-21:00 | 0.53 | 0.49–0.58 | 0.51 | 0.47–0.57 | 0.50 | 0.41–0.68 |
|    | 21:00-00:00 | 0.58 | 0.55–0.63 | 0.59 | 0.56–0.63 | 0.84 | 0.61–1.25 |
| γ  | 00:00-05:00 | –0.04 | –0.12–0.02 | 0.02 | –0.01–0.06 | – | – | – |
|    | 05:00-07:00 | 0.02 | –0.03–0.08 | – | – | 0.08 | 0.01–0.14 |
|    | 07:00-10:00 | –0.04 | –0.11–0.01 | – | – | 0.00 | –0.03–0.02 |
|    | 10:00-16:00 | 0.01 | –0.01–0.03 | – | – | 0.00 | –0.03–0.02 |
|    | 16:00-21:00 | 0.02 | –0.03–0.05 | 0.00 | –0.05–0.05 | –0.01 | –0.20–0.08 |
|    | 21:00-00:00 | 0.00 | –0.04–0.02 | –0.03 | –0.06–0.00 | –0.24 | –0.64–0.01 |
| VT | 00:00-05:00 | 0.15 | 0.12–0.20 | 0.09 | 0.07–0.12 | – | – | – |
|    | 05:00-07:00 | 0.13 | 0.11–0.17 | – | – | 0.18 | 0.12–0.27 |
|    | 07:00-10:00 | 0.15 | 0.10–0.24 | – | – | 0.10 | 0.04–0.18 |
|    | 10:00-16:00 | 0.06 | 0.03–0.10 | – | – | 0.09 | 0.06–0.13 |
|    | 16:00-21:00 | 0.17 | 0.13–0.24 | 0.14 | 0.09–0.21 | 0.15 | 0.05–0.37 |
|    | 21:00-00:00 | 0.13 | 0.10–0.16 | 0.10 | 0.07–0.13 | 0.28 | 0.12–0.54 |

**Abbreviations:** Est.: coefficient estimate, 95% CI: 95% Confidence Interval, α, γ, and VT are predictor coefficients (see Table 4 for VC equation).
In case of multiple taxi occupancy, the formulation of the VC can be modified by adding a new parameter ($\zeta$) which indicates the number of additional passengers to the first passenger ($P-1$). As a result, the VC formulation given in the Table 4 and Eq. (2) became Eq. (7) and Eq. (8) respectively, as follows:

$$VC = \alpha + \gamma e^{\left(\frac{TT}{ST}-1\right)} + \zeta e(P-1)$$  \hspace{1cm} (7)

$$\Delta Fare_{i, pas} = \left(\alpha + \gamma e^{\left(\frac{TT_i}{ST_i}-1\right)} + \zeta e(P-1)\right) * TT_{i} + VT * (ST_{i} - TT_{i})$$  \hspace{1cm} (8)

where $\Delta Fare_{i, pas}$ is the per passenger fare difference between taxi trip $"i"$ and an equivalent subway trip (i.e., total taxi fare divided by number of passengers minus $2.75$ subway fee), $\zeta$ is the additional parameter, and $P$ is the number of taxi passenger. The Eq. (8) is further simplified by dividing both sides by the taxi travel time (Eq. (9)):

$$\Delta Fare_{i, pas} / TT = \left(\frac{\alpha + \gamma e^{\left(\frac{TT_i}{ST_i}-1\right)} + \zeta e(P-1)}{TT_i}\right) + VT * (\frac{ST_{i}}{TT_{i}} - 1)$$  \hspace{1cm} (9)

### Table 7
Parameter estimates for the Non-CBD zone.

| Time of Day | Weekday | 95% CI | Social | 95% CI | Weekend | 95% CI |
|-------------|---------|--------|--------|--------|---------|--------|
| $\alpha$ 00:00-05:00 | 0.47 | 0.34 | 0.85 | 0.31 | 0.25 | 0.39 | 
| 05:00-07:00 | 0.39 | 0.27 | 0.52 | - | - | - | 0.28 | 0.10 | 0.55 |
| 07:00-10:00 | 0.48 | 0.44 | 0.58 | - | - | - | 0.36 | 0.25 | 0.57 |
| 10:00-16:00 | 0.59 | 0.55 | 0.67 | - | - | - | 0.56 | 0.52 | 0.60 |
| 16:00-21:00 | 0.48 | 0.43 | 0.59 | 0.45 | 0.41 | 0.50 | 0.34 | 0.28 | 0.42 |
| 21:00-00:00 | 0.59 | 0.51 | 0.77 | 0.59 | 0.53 | 0.66 | 0.55 | 0.44 | 0.70 |
| $\gamma$ 00:00-05:00 | -0.01 | -0.37 | 0.12 | 0.13 | 0.06 | 0.19 | 
| 05:00-07:00 | 0.15 | 0.04 | 0.28 | - | - | - | 0.27 | 0.04 | 0.47 |
| 07:00-10:00 | -0.02 | -0.12 | 0.04 | - | - | - | 0.11 | -0.15 | 0.23 |
| 10:00-16:00 | -0.01 | -0.10 | 0.04 | - | - | - | 0.04 | 0.00 | 0.08 |
| 16:00-21:00 | 0.07 | -0.05 | 0.13 | 0.08 | 0.03 | 0.13 | 0.15 | 0.07 | 0.22 |
| 21:00-00:00 | 0.01 | -0.16 | 0.09 | 0.02 | -0.04 | 0.08 | 0.05 | -0.09 | 0.16 |
| $VT$ 00:00-05:00 | 0.14 | 0.08 | 0.32 | 0.09 | 0.06 | 0.13 | 
| 05:00-07:00 | 0.08 | 0.02 | 0.15 | - | - | - | 0.01 | -0.10 | 0.16 |
| 07:00-10:00 | 0.15 | 0.09 | 0.27 | - | - | - | 0.11 | -0.01 | 0.39 |
| 10:00-16:00 | 0.10 | 0.06 | 0.17 | - | - | - | 0.08 | 0.05 | 0.12 |
| 16:00-21:00 | 0.15 | 0.10 | 0.27 | 0.11 | 0.07 | 0.16 | 0.04 | -0.02 | 0.12 |
| 21:00-00:00 | 0.13 | 0.08 | 0.23 | 0.11 | 0.08 | 0.15 | 0.11 | 0.05 | 0.18 |

**Abbreviations**: Est.: coefficient estimate, 95% CI: 95% Confidence Interval, $\alpha$, $\gamma$, and $VT$ are predictor coefficients (see Table 4 for VC equation).

### Table 8
Parameter ($\zeta$ and $VT$) estimates of the modified model.

| Time of Day | CBD Weekday | Social | Weekend | Non-CBD Weekday | Social | Weekend |
|-------------|-------------|--------|---------|-----------------|--------|---------|
| $\zeta$ 00:00-05:00 | -0.15 | -0.15 | - | -0.16 | -0.16 | - |
| 05:00-07:00 | -0.19 | - | -0.20 | -0.20 | - | -0.20 |
| 07:00-10:00 | -0.12 | - | -0.13 | -0.13 | - | -0.14 |
| 10:00-16:00 | -0.15 | - | -0.17 | -0.17 | - | -0.18 |
| 16:00-21:00 | -0.14 | -0.13 | -0.13 | -0.15 | -0.14 | -0.14 |
| 21:00-00:00 | -0.19 | -0.17 | -0.19 | -0.21 | -0.21 | -0.21 |
| $VT$ 00:00-05:00 | 0.09 | 0.03 | - | 0.09 | 0.04 | - |
| 05:00-07:00 | 0.09 | - | 0.13 | 0.01 | - | -0.05 |
| 07:00-10:00 | 0.07 | - | 0.04 | 0.09 | - | 0.04 |
| 10:00-16:00 | 0.00 | - | 0.04 | 0.04 | - | -0.01 |
| 16:00-21:00 | 0.09 | 0.07 | 0.06 | 0.08 | 0.03 | -0.01 |
| 21:00-00:00 | 0.06 | 0.03 | 0.14 | 0.08 | 0.06 | 0.07 |

**Abbreviations**: $\zeta$ and $VT$ are predictor coefficients (see Eq. (6) in the Appendix B).
Table 9
Summary comparison of parameter (α and γ) estimates.

| % Change | CBD | Non-CBD |
|----------|-----|---------|
| Mean:    | −10.0% | 4.4%  | −0.6%  | −0.8%  |
| Std. Dev.: | 6.8% | 65.6% | 8.4%  | 32.5%  |
| Median:  | −9.1% | 0.0%  | 0.0%  | 0.0%  |

\[
\frac{\Delta \text{Fare}_{i,p}}{\text{TT}_{i}} = \alpha + \gamma i \left( \frac{\text{TT}_{i}}{\text{P}-1} \right) + \zeta i (P - 1) + \text{VT}_{i} \left( \frac{\text{ST}_{i}}{\text{TT}_{i}} - 1 \right) \quad (9)
\]

The model parameters (α, γ, ζ, and VT) are estimated using multilevel modeling approach as described in the “Final Value of Time and Convenience Model” section. The results of the modified model are presented in two tables: 1) Table 8 shows the parameter estimates for ζ and VT, 2) Table 9 shows summary of changes in parameter estimates (α and γ) with respect to results given in the Appendix A. That is, the results for α and γ is close to the estimates without “per passenger” modification; hence, only summary descriptive statistics are given for the sake of simplicity. Theoretically, we expected that each additional passenger in a taxi would potentially reduce the value of convenience due to the crowding. The analysis result supports this expectation as the ζ parameter estimated to be −0.15 on average, indicating that each additional passenger (to the first passenger) reduce the VC about $0.15 per minute travel. For example, the value of convenience of a 30 min taxi trip with 2 passengers would be $4.50 (0.15 × 30 × (2–1)) lower than a single passenger taxi trip, while VC of a 3 passenger trip would be $9.00 lower (See Tables 9).

References
Al-Ayyash, Z., Abou-zeid, M., Kaysi, I., 2016. Modeling the demand for a shared-ride taxi service: An application to an organization-based context. Transp. Policy 48, 169–182. https://doi.org/10.1016/j.tranpol.2016.02.013.
Anderson, R., Condy, B., Findlay, N., Brage-Ardo, R., Li, H., 2013. Measuring and Valuing Convenience and Service Quality, in: International Transport Forum.
Batare, M., Carlos, J., Dios, J.D., 2016. Valuing crowding in public transport: Implications for cost–benefit analysis. Transp. Res. Part A 91, 358–378. https://doi.org/10.1016/j.tra.2016.06.025.
Burnham, K.P., Anderson, D.R., 2002. Model Selection and Multimodel Inference. Springer.
Carrion, C., Levinson, D., 2012. Value of travel time reliability: A review of current evidence. Transp. Res. Part A 46, 720–741. https://doi.org/10.1016/j.tra.2012.01.003.
Cox, T., Houdmont, J., Griffiths, A., 2006. Rail passenger crowding, stress, health and safety in Britain. Transp. Res. Part A 40, 244–258. https://doi.org/10.1016/j.tra.2005.07.001.
Crockett, J., Houmeso, N., 2005. Role of the travel factor convenience in rail travel and a framework for its assessment. Transp. Rev. 25, 535–555. https://doi.org/10.1080/01441640500064389.
Ebeli, L., Mazzulla, G., 2008. Willingness-to-pay of public transport users for improvement in service quality. Eur. Transp. 38, 107–118.
Englisher, L.S., 1984. Late-Night Shared-Ride Taxi Transit in Ann Arbor, Michigan. UMTA-MA-06-0049-84-7.
Gandhi, S.J., Gorod, A., Sauser, B., 2011. A case study: The New York City yellow cab System of Systems. In: Proc. 2011 6th Int. Conf. Syst. Syst. Eng. SoSE Cloud Comput. Smart Grid, Cyber Secur. SoSE 2011 282.
Gelman, A., 2006. Multilevel (hierarchical) modeling: What It can and cannot do. Technometrics 48, 432.
Haywood, L., Koning, M., Monchambert, G., 2017. Crowding in public transport: Who cares and why? Transp. Res. Part A 100, 215–227. https://doi.org/10.1016/j.tra.2017.04.022.
Huey, J.A., Everett, P.B., 1996. Immediate benefits: The reason for the car’s success and transit’s failure. Transp. Res. Rec. J. Transp. Res. Board 1521. doi:10.1177/0361198196152100109.
Jones, A.P., Jorgensen, S.H., 2003. The use of multilevel models for the prediction of road accident outcomes. Accid. Anal. Prev. 35, 59–69. https://doi.org/10.1016/S0001-4575(01)00068-0.
Kim, K., 2018. Exploring the difference between ridership patterns of subway and taxi: Case study in Seoul. J. Transp. Geogr. 66, 213–223. https://doi.org/10.1016/j.jtra.2017.12.003.
Krygsman, S., Dijst, M., Arentze, T., 2004. Multimodal public taxi: An analysis of travel time elements and the interconnectivity ratio. Transp. Policy 11, 253–262. https://doi.org/10.1016/j.tranpol.2003.12.001.
Lam, T.C., Small, K.A., 2001. The value of time and reliability: measurement from a value pricing experiment. Transp. Res. Part E 37, 231–251.
Li, Z., Hensher, D.A., Rose, J.M., 2014. Willingness to pay for travel time reliability in passenger transport: A review and some new empirical evidence. Transp. Res. Part E 46, 384–403. https://doi.org/10.1016/j.trse.2009.12.005.
Litman, T., 2008. Valuing Transit Service Quality Improvements. J. Public Transp. 11, 43–63.
Middendorf, D.P., Heathington, K.W., Davis, F.W.J., 1975. An Analysis of the Demand for Bus and Shared-Ride Taxi Service in Two Smaller Urban Areas. UMTA-TN-56-004-75-1.
Nam, D., Park, D., Khamkongkhun, A., 2005. Estimation of Value of Travel Time Reliability. J. Adv. Transp. 39, 39–61.
Neuman, W., 2008. In Decade of Unlimited Rides, MetroCard Has Transformed How the City Travels [WWW Document]. New York Times. URL https://www.nytimes.com/2008/07/16/nyregion/16metrocard.html (accessed 6.8.20).

NYC, 2020a. TLC Trip Record Data [WWW Document]. Taxi Limousine Comm. URL https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page.

NYC, 2020b. Taxi Fare - Standard Metered Fare [WWW Document]. Taxi Limousine Comm. URL https://www1.nyc.gov/site/tlc/passengers/taxi-fare.page#:~:text=%242.50%20initial%20charge.,Dutchess%2C%20Orange%20or%20Putnam%20Counties.

Paraboschi, A., Santi, P., Ratti, C., 2015. Modeling urban-level impact of a shared taxi market. In: CUPUM 2015 - 14th International Conference on Computers in Urban Planning and Urban Management. pp. 1–23.

Portland Bureau of Transportation, 2018. 2018 E-Scooter Pilot User Survey Results. Portland, Oregon.

Schaller, B., 2017. Empty Seats, Full Streets. Fixing Manhattan’s Traffic Problem.

Senna, L.A.D.S., 1994. The influence of travel time variability on the value of time. Transportation (Amst). 21, 203–228. https://doi.org/10.1007/BF01098793.

Small, K.A., 2012. Economics of Transportation Valuation of travel time. Econ. Transp. 1, 2–14. https://doi.org/10.1016/j.ectra.2012.09.002.

State of New York, 2019. Joint Senate-Assembly budget legislation, 1509c.

Teal, R.F., Marks, J.V., Goodhue, R.E., 1980. Subsidized shared-ride taxi services. Transp. Res. Rec. 778, 25–32.

Tirachini, A., Hensher, D.A., Rose, J.M., 2013. Crowding in public transport systems: Effects on users, operation and implications for the estimation of demand. Transp. Res. Part A 53, 36–52. https://doi.org/10.1016/j.tra.2013.06.005.

Trompet, M., Parasram, R., Anderson, R.J., 2013. Benchmarking disaggregate customer satisfaction scores of bus operators in different cities and countries. Transp. Res. Rec. J. Transp. Res. Board 2351, 14–22. https://doi.org/10.3141/2351-02.

Verplanken, B., Aarts, H., van Knippenberg, A., van Knippenberg, C., 1994. Attitude versus general habit: antecedents of travel mode choice. J. Appl. Soc. Psychol. 24, 285–300.

Wardman, M., 2014. Valuing Convenience in Public Transport, in: International Trans.

Whelan, G., Crockett, J., 2008. An Investigation Overcrowding of the Willingness to Pay to Reduce Rail, in: First International Conference on Choice Modelling. Harrogate, England.

Yao, B., Hu, P., Lu, X., Gao, J., Zhang, M., 2014. Transit network design based on travel time reliability. Transp. Res. Part C 43, 233–248. https://doi.org/10.1016/j.trc.2013.12.005.