Dynamics of supply and demand for competing shared mobility services

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June 24, 2025

Introduction

Travel demand models typically include transportation supply options (e.g., drive, transit, walk/bike) whose characteristics are largely exogenous. But today, there are travel options, such as on-demand shared mobility services, which respond, in near-real time, to market cues. In some cities, such services account for a substantial portion of traffic and resulting congestion, particularly in central business districts. A survey of vehicles in New York City's borough of Manhattan revealed that for-hire vehicles (including transportation network company (TNC) vehicles plus taxis) made up approximately half of the traffic sampled (NYC Taxi and Limousine Commission and DOT 2019). TNCs, who typically pay contractors on a trip-by-trip basis to use their own vehicles to pick up and drop off travelers who book trips via mobile application, were also found to be a substantial contributor to traffic congestion in San Francisco (Erhardt et al. 2019). Therefore, it matters that these travel options are not well-modeled.

In some cases, vendors of trips compete for shared resources. For example, TNCs, such as Uber and Lyft, compete for drivers, and we can envision a possible future world in which shared mobility services using automated driving systems (ADS) compete for available vehicles. Not only do shared mobility services, whether TNC or automated, compete for travel supply, but this competition affects the price offered to would-be travelers in near-real time, with accompanying effect on user response. It is perhaps not a surprise that travel demand models struggle to account for the behavior of travel options that have this real-time feedback. While the literature does address how drivers respond to the driver pay offered, and, separately, how users respond to the price of a trip, current models do not represent the complete feedback loop.

In a multi-operator shared mobility environment, several TNC operators compete for both drivers (supply) and travelers (demand), creating a complex system of interdependent relationships. This includes how travelers respond to operational strategies; how drivers make choices in response to these strategies; and how operators adjust their strategies based on demand and supply conditions.

Several studies focus on how users respond to operator strategies. Wang, Correia, and Lin (2022) developed a multinomial logit model in an agent-based modeling framework to examine how travelers adjust their decisions based on fleet size, fare structures, and assignment strategies of different operators. However, this study does not capture competition between operators, or operator-side responses to demand. Similarly, Wong et al. (2024) used a logit-based discrete choice model calibrated from a stated preference survey collected in Hong Kong to study shared mobility acceptance in the context of app-based car-pooling and taxi ride-sharing. They identified key factors that influence traveler and driver decisions, but did not address how operators react to changes in demand.

Other studies emphasize how TNC drivers respond to operators' strategies. Guo et al. (2023) applied a Bayesian estimation-based structural model to investigate the behavior of freelance drivers in multi-operator environments, particularly decisions of drivers regarding switching between platforms or operating across multiple services. While this study captures the interaction between driver behavior and operator strategy, it does not explicitly model demand responses or inter-operator competition. Regarding the operator-side response to demand fluctuations, Martin (2022) examined how operators adjust strategies in response to spatio-temporal variations in demand, by implementing fleet rebalancing strategies. However, this study focuses on operational decisions and fleet-based ownership, and does not consider further demand feedback to operator strategies, nor systems, such as typical human-driven TNCs, where each driver owns their own vehicle.

While these studies provide insights into individual components of demand-supply interactions in a multi-operator shared mobility environment, they fail to capture the complete feedback loop—where user responses impact drivers; drivers impact operator strategies; and operators in turn influence both users and drivers. Additionally, the models mentioned above primarily focus on short-term operational strategies, such as ride assignment and pricing decisions, rather than long-term planning, such as fleet size optimization in a competitive TNC landscape.

To address multi-operator competition, some studies explore strategic interactions between operators in shared mobility markets. Huang, Ding, and Jian (2024) introduced a game-theoretic model to study cooperative competition between transportation service providers, analyzing resource-sharing and price-setting decisions. While the study captures interactions between operators, and supply-demand characteristics, it focuses on markets such as electric vehicle charging stations and hence has limited applicability in shared mobility markets which have dynamic spatio-temporal demand and supply variations. Jiang and Ouyang (2022) used Generalized Nash Equilibrium models to study competition in the context of docked bike-sharing systems, examining fleet sizing, station locations, and pricing decisions over short time periods (hours in a day). Pandey et al. (2019) employed optimization models to analyze the impact of competition and cooperation in ridesharing, finding that competition can degrade service quality, particularly when operators prioritize their own optimization over system-wide efficiency.

Despite these contributions, existing studies primarily address real-time operational decisions and individual aspects of demand-supply endogeneity. They do not simultaneously capture the full feedback loop where users, drivers, and operators continuously influence each other. Furthermore, most models focus on immediate operational adjustments rather than long-term fleet planning, making them unsuitable for strategic decision-making in a competitive multi-operator TNC environment.

System dynamics (SD) modeling offers a promising approach for strategic planning in multi-operator TNC markets by capturing the full feedback cycle between demand, supply, and operator competition. However, there is very limited literature employing SD models in this context. One relevant study is by Ruutu, Casey, and Kotovirta (2017). Their study explores how digital service platforms evolve and compete, using the case study of what they call mobility-as-a-service platforms. It examines the interactions between platform providers and users, emphasizing the role of network effects, platform innovation, and competition strategies. The study highlights how factors like pricing, investment in innovation, and user adoption influence platform dominance or failure. By simulating different scenarios, the research provides insights into strategic decisions that platforms can take to sustain growth and outperform competitors in a rapidly evolving market. However, while the study effectively evaluates the evolution of operator market shares, it does not delve into specific mid-term operational decisions service providers must make, such as fleet size planning or resource allocation.

There remains a critical gap in understanding the effects of the decisions of shared-mobility operators and of travelers on fleet sizes, traveler mobility, and congestion. Current literature does not comprehensively capture the endogeneity of feedback between both demand and supply of trips on the operator's side – that is, between the operator adjusting prices to bring in more or fewer human-driven or ADS trips - and between demand and supply seen from the traveler's perspective - that is, between wait times and mode choice. The model developed here, however, shows how a decision on one side impacts a decision on the other. It further represents the feedback between multiple operators (such as, for example, Uber and Lyft) who are competing for both drivers and customers.

By integrating demand-side responses, driver behavior, and operator strategies, the present model provides a long-term planning framework for multi-operator TNC markets. It can point towards how anyone looking to offer a shared mobility service – with or without automated driving – can strategically plan fleet sizes while responding to both demand fluctuations and competitive interactions. Furthermore, it can help cities estimate how vehicle miles travelled attributable to shared mobility may change if ADS-based shared mobility services are deployed in their communities.

Approach

The model presented in this paper represents vendors' competition for both supply (trips offered by drivers or ADS vehicles) and demand (traveler trips), shown as one complete loop, to reflect not only competition among vendors but also induced trips and demand-mediated changes in the price of adding trip capacity. While fare is still exogenous, scenarios address several business models, such as a vendor who aims to make money off of high volume, and one who aims to maximize profit per trip. (In the model, the term vendor, rather than operator, is used, to align with larger literature on multi-vendor competition.)

A stock-flow model represents the offerings of several providers of shared mobility services, and how they might respond to market cues. The supply side of the model includes a common pool of regional shared mobility resources (e.g., drivers and vehicles, with capacity represented as trips per month); and several service vendors with their own characteristics (fare, cost structure, and target utilization in terms of trips served divided by trip capacity). The demand side of the model includes traveler wait time for each vendor, which is a function of vendor characteristics and the number of travelers. Wait time feeds into a simple nested logit model that first considers traveler response to the several shared mobility vendors, and then the competition between shared mobility, other modes, and whether or not trips are made - that is, the level of induced travel.

Figure 1 shows the entire stock-flow diagram.

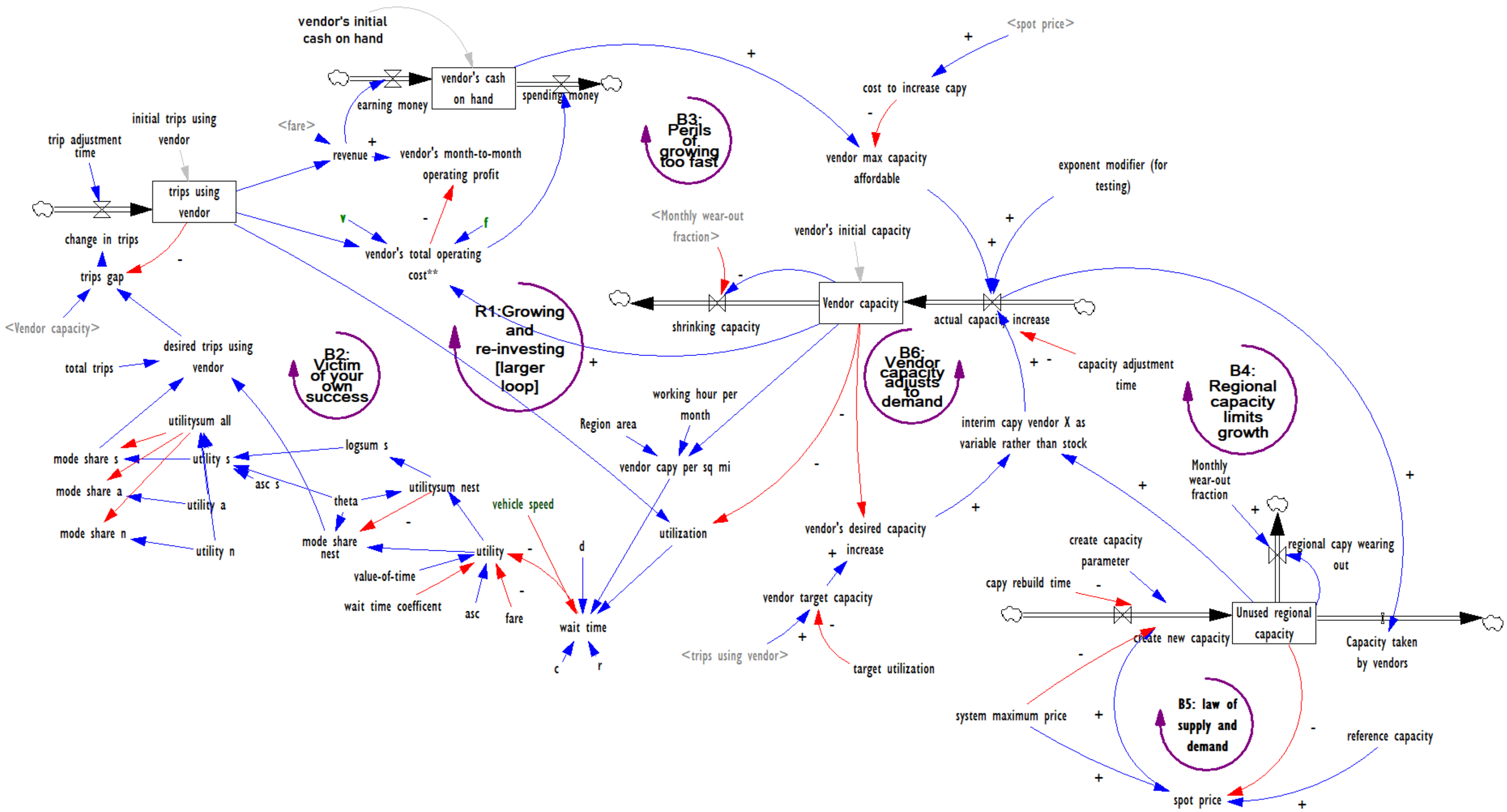

Figure 1 Model diagram

Feedback loops

Six key loops, one reinforcing and five balancing, comprise the model.

The first three loops focus on the vendor's business choices:

Reinforcing loop 1: Growing and re-investing

Each vendor begins with a certain number of trips served per month ("trips using vendor"). From this, they earn revenue, which increases their cash on hand. More cash on hand leads to a higher maximum capacity that they can afford ("vendor max capacity affordable"). This feeds the vendor's capacity increase, which in turn reduces the fraction of that vendor's capacity that is used (the vendor's utilization). A lower utilization leads to a lower wait time, which improves the vendor's utility in the eyes of potential customers. Higher utility means a higher mode share and more travelers wishing to take trips ("desired trips using vendor"), and thus, a higher number of trips served.

Balancing loop 2: Victim of your own success

However, serving a higher number of trips means that the vendor's utilization increases. This, all else being equal, lengthens the wait time, leading to lower utility, lower mode share, and lower desired and actual trips using that vendor.

Balancing loop 3: Perils of growing too fast

If the vendor's cash on hand increases, the maximum capacity that the vendor can afford and the vendor's (actual) capacity also increase. But supporting all that capacity costs money, so the vendor's total operating cost increases, leading to them spending more money, which in turn reduces their cash on hand.

The remaining three loops address the details of how unused regional capacity interacts with vendors' desires to add (or, indeed, drop) capacity. Vendors looking to increase their capacity all compete for a common stock of unused regional capacity. This reflects the fact that many TNC drivers are willing and able to drive for both Uber and Lyft, and may in fact be selling trips to both within the same month (or even within the same day). And companies purchasing ADS-enabled vehicles will be competing for ADS vehicles or for trips using non-company-owned vehicles, at least during an initial period when manufacturing is still ramping up.

Balancing loop 4: Regional capacity limits growth

The higher the sum of actual capacity increase by all vendors, the greater the capacity taken by vendors, so the stock of unused regional capacity goes down. All else equal, this leads to a lower rate of actual capacity increase.

Balancing loop 5: Law of supply and demand

However, all else is not equal. As the stock of unused regional capacity decreases in relation to a fixed reference capacity, the cost of each unit of remaining available capacity (the "spot price") increases. This represents both surge pricing in today's world, as well as a presumed increase in unit price of ADS-enabled vehicles in times of vehicle shortage. As spot price rises in the ADS world, vehicle developers and manufacturers should take note, seeking to ramp up production. And in the human-driven world, more drivers are tempted to sign up to drive, thus creating new capacity. This is somewhat of a simplification of how surge pricing works, since surge pricing operates on a much shorter timescale than trips per month and is intended to attract more drivers to sign in at that moment for a particular vendor, rather than to enter the overall pool of TNC drivers writ large.

Balancing loop 6: Vendor capacity adjusts to demand

This loop returns to the dynamics of individual vendors. As a particular vendor's capacity increases, their desired capacity increase diminishes, because the gap has narrowed between their current capacity and their target capacity, which is determined by the degree to which their existing capacity is being utilized. A lower desired capacity increase means a lower rate of actual capacity increase (via a mechanism mediated by the amount of unused regional capacity remaining). This slows the growth of the stock of the vendor's capacity.

Calibrating the model for the human-driven world

Publicly-available data for TNC trips in the five boroughs of New York City provided a rich dataset to establish a reference mode and permit calibration of the model. The city's Taxi and Limousine Commission (TLC) records and posts publicly the following information for each TNC trip originating in New York City:

- Origin zone (New York tracks trip origin and destination by taxi zones, a list of 265 sub-areas across the five boroughs.)
- Destination zone
- Date and time of trip
- Trip time and mileage
- Waiting time
- Price charged to the traveler
- Driver pay

Some TNC trips with pick-ups in New York City, thus making them subject to TLC tracking, end outside the city, in an “Outside of NYC” zone. Newark Airport, while not within New York City, is also a taxi zone in the data, and trips originating there are also included. For the present analysis, we grouped trips into a smaller set of analysis zones: Upper Manhattan, Lower Manhattan, Brooklyn, Bronx, Queens, Staten Island, and the region’s three major airports (JFK, LaGuardia, and Newark Airport), plus a zone for all other non-NYC destinations.

Using the approximately 19 million TNC trips recorded in New York City in September 2024, we calculated the number of trips beginning within each hour-long period (summed across the month) for each origin-destination pair of analysis zones. For example, for all days of September 2024 combined, 9,659 TNC trips traveled from the Bronx to Lower Manhattan with origin times between 00:00 and 00:59 inclusive. These calculations grouped the 19 million trips into slightly more than 2,000 records. For each line, we calculated mean trip distance, mean trip duration, mean total price of the trip (before any tip paid to the driver), the mean wait time for the passenger, and the mean pay the driver received (again, excluding any tip).

The TLC reports, at an aggregate level, the number of vehicles registered for TNC service, as well as their average utilization (time with a passenger divided by total on-duty time). However, the data does not include information on the number, distance, or distribution of repositioning – the mileage that TNC drivers drive without a passenger, to pick up their next fare. The public data also does not include any unique driver identifier, so the total number of drivers working at any one point is not directly revealed. While these gaps may be understandable from the perspectives of protecting corporate-sensitive trip-assignment algorithms and driver privacy, they nevertheless represent significant hurdles for modeling the system.

We estimated the amount and distribution of repositioning trips by looking at the imbalances between loaded trips into and out of each zone. For example, trips into Lower Manhattan during the morning rush hour exceed those headed out. For each morning hour, the imbalance reveals how many empty vehicles, on average over the month, must have left Lower Manhattan empty in order to bring back the next load of commuters or shoppers. The imbalances are pairwise among zones, so the empty repositioning trips can be assigned not only to Lower Manhattan as origin, but also to a destination borough. With this analysis, interborough and airport empty repositioning miles were found to total approximately 15% of the number of loaded miles, thus representing about 13% of total miles. The imbalance was greatest in early morning. From 5:00 - 5:59 AM, empty miles represent about 33% of total miles, an imbalance driven largely by many loaded trips going to the airports but few TNC passengers leaving airports. Empty miles were lowest around 6 PM, with trips more-or-less evenly distributed across the boroughs.

The imbalance analysis yielded the total number of trips (loaded and empty repositioning) for each origin-destination pair, for each of the 24 hours of the day. Assuming an average borough-to-borough trip distance for each pair yielded an estimate of the total miles driven by TNCs – both with and without passengers - each hour. From this we derived an hourly estimate of the TNC fleet size active in New York City.

We also examined patterns in travelers' wait times, finding

- An average of approximately 5 minutes
- Some variability due to both the number of trips between specific boroughs, during specific hours (fewer trips tend to be correlated with slightly longer wait times)
- Some variability due to empty imbalances (more trips leaving than entering the analysis zone was associated with longer wait times). This was especially true for the airports late in the evening.

Based on this analysis, the wait time model in the system dynamics model has three elements

- A constant term, set to 3 minutes
- A term that approximates the traveler's wait for an empty vehicle. By a fundamental result from queuing theory, it is proportional to $\frac{1}{1-Vehicle\ Utilization}$. At 0.72 utilization (defined as trips / capacity, and calculated from the data as (loaded+empty time) / total time), this term contributes about 2.7 minutes to the wait time. To avoid divide-by-zero issues, this term is capped at 120 minutes.
- A term that is proportional to $1/\sqrt{trip\ density}$ which contributes between 0.3 and 0.5 minutes to the wait time. In a situation where available vehicles are randomly and evenly distributed over a region, the expected distance to the nearest available vehicle is proportional to a constant divided by the square root of the number of vehicles. This is 0.5 / $\sqrt{n}$ (straight line distance), or approximately 0.625 / $\sqrt{n}$ (right angle distance) where n is the number of available vehicles per square mile (Larson and Odoni 1981, p. 151).

The system dynamics model includes a simple nested logit travel demand model. At the top level, there are two travel modes, shared mobility (denoted by *s*) and everything else (*a*). A third "mode" (*n*) represents a pool of trips, currently not taken, that could be taken should the travel options become more attractive (e.g., a substantial reduction in fare for a shared mobility option).

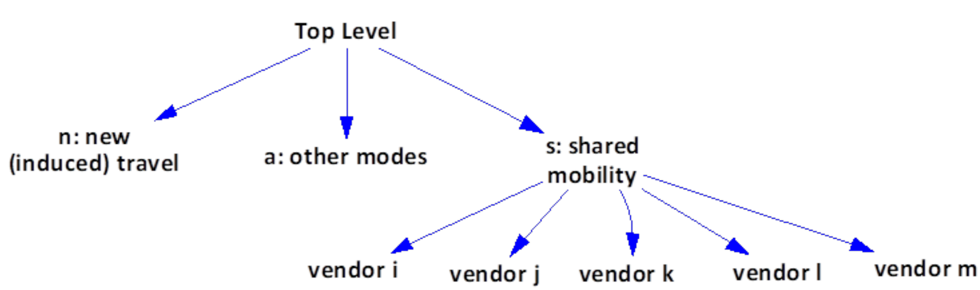

Figure 2 Nesting structure for the travel demand model

Looking towards impacts of a potential deployment of ADS vehicles in TNC service, the model was calibrated to produce a pool of potential additional trips from which induced travel can be drawn. Based on the suggestion in Stephens et al. (2016) of a potential 20-percent increase in overall travel resulting from increased travel by the transportation-disadvantaged, this pool was set at 20 per cent of existing trips. Additional evidence of potential induced travel comes from Harper et al. (2016), who reviewed data from the 2009 National Household Travel Survey, comparing overall travel with the amount of travel by the elderly, non-motorists, and those with travel-restrictive conditions. They noted that "If ADS-equipped vehicles enable the amount of travel by these populations to increase to the amount of travel (VMT) observed in the remainder of the population, overall annual light-duty VMT could increase by 14 percent."

The resulting system dynamics model was calibrated for the reference mode of New York City in September 2024. New York's data also records for each trip whether it was taken using Uber or via Lyft, the only two TNCs operating in New York City at that point. While overall dead-heading miles and trips were calculated for all vendors together (since drivers can switch between the two platforms throughout the day), the vendor-specific trip totals were used for the reference mode. We refined wait time, cost structure and mode choice assumptions in the system dynamics model to yield these trip totals in equilibrium. To calibrate the mode choice part of the model, we took advantage of publicly-available high-level ridership data from New York's Metropolitan Transportation Authority (MTA), as well as the results of a recent city-wide travel survey. Among the motorized-trips surveyed (including transit, but excluding walk and bike), TNC trips represented about 4% of the total.

The appendix provides a full model description and complete initial values.

Experiments and results

After calibration with the new incumbent vendors (vendor i, representing Uber, and vendor j, representing Lyft), a new vendor, k, was added. Two experiments were performed with that vendor. In both experiments, the vendor started with a low initial capacity (600,000 trips / month). Some have argued that ADS may lead to lower fares, so we tested two notional lower-fare scenarios.

- Experiment 1 gave vendor k similar characteristics to vendor j, except for a slightly lower fare ($35 rather than $38)
- Experiment 2 reduced both the variable cost and the fare considerably for vendor k, compared to the incumbent vendors. Variable cost per trip was reduced from $28 to $18. Fare was reduced from $38 to $25.

Vendor k begins each experiment with no trips; it must build its market share.

Figure 3 shows the trips using each vendor, as a monthly time series over a 5-year (60-month period). The reference mode (before vendor k is introduced) shows a nearly constant number of trips for vendors i and j; vendor k does not appear in the reference mode.

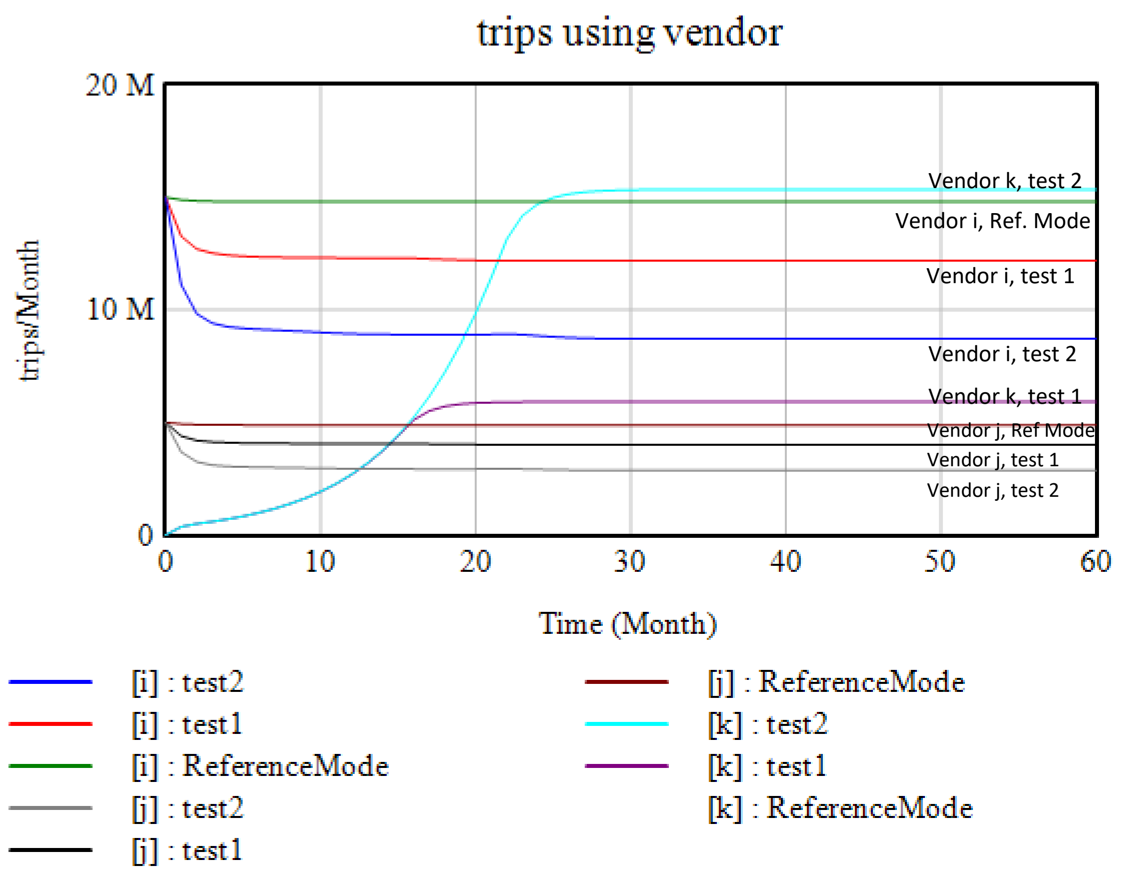

Figure 3 Trips using vendor

The results labeled test1 and test2 show the growth in trips for vendor k, taking market share from the incumbents in each of the two experiments run. Table 1 shows the trips at the start and end of the simulation. Test 1 adds approximately 2.4 million TNC trips, of which 1.9 million came from other modes, while 0.5 million are new trips. Test 2 adds approximately 7.2 million TNC trips, of which 5.7 million came from other modes, and 1.5 million are new.

Table 1 TNC trips

		Monthly trips (millions)					
Experiment	**Vendor**	**Start at month 0**	**End at month 60**	**Total TNC trips at end**	**Difference from reference mode**	**New trips**	**Trips shifted from other modes**
ReferenceMode	I	15	14.811				
ReferenceMode	J	5	4.888	19.698	n/a	n/a	n/a
test1	I	15	12.184				
test1	J	5	4.018				
test1	K	0	5.919	22.121	2.423	0.500	1.923
test2	I	15	8.712				

		Monthly trips (millions)					
Experiment	**Vendor**	**Start at month 0**	**End at month 60**	**Total TNC trips at end**	**Difference from reference mode**	**New trips**	**Trips shifted from other modes**
test2	J	5	2.869				
test2	K	0	15.352	26.933	7.234	1.490	5.744

Each vendor's desired utilization was set so that average wait times would be about 5 minutes, similar to what was observed in the data. Figure 4 shows the evolution in wait times. For the reference mode, the wait times stay constant at about 5 minutes. When the new vendor is introduced, it takes between 20 and 26 months to restore the equilibrium.

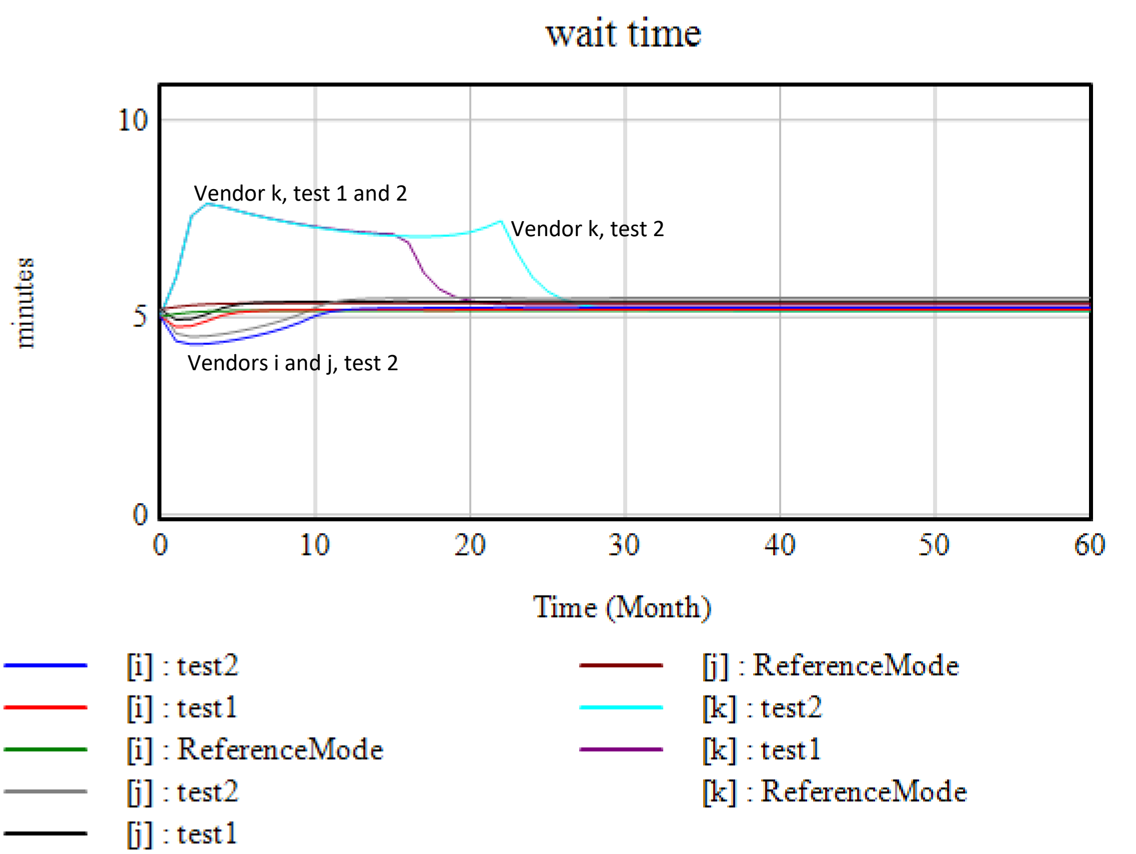

Figure 4 Wait time

Several mechanisms lead to this result:

1. The legacy vendors (i, j) now have a new competitor. Their utilization declines, with a corresponding short-term reduction in wait time for their services. Eventually, they shed trip capacity in response to this loss of business, and the desired utilization (with resulting wait time of about 5 minutes) is restored.

2. Meanwhile, the new vendor (k) is trying to grow, but is constrained by available funding, and the lag in acquiring trip capacity. Therefore, vendor k's utilization and resulting wait time start off high, until vendor k's capacity has grown enough to serve the new split in demand among the three vendors, at which point utilization has reached vendor k's desired level and wait times stabilize.
3. The spike at month 23 for test 2 with vendor k represents an interaction with the common pool of supply and the spot price. In this case, the vendor is drawing down from the common pool of supply until the stock of unused common capacity is low enough to trigger an increase in the spot price after month 21. This further constrains vendor k's ability to grow, leading to an increase in its utilization and wait time. Eventually, vendor k's growth slows, the market readjusts, and the vendor's desired utilization (with a resulting wait time of 5 minutes) is reached.

Discussion

This endogenous model of transportation supply with multiple service providers includes (1) competition for upstream resources, (2) competition for customers, and (3) traveler responses to the offered services. It allows for recalculation of NYC data attributes at an aggregate level to account for different scenarios of price of travel and level of service; outputs include implications for congestion and wait time. The stock-flow model runs by itself, or it can be integrated with the U.S. Department of Energy's POLARIS agent-based model of travel supply and demand, which allows for much more detailed modeling of traveler response to changes in supply. Either way, the model provides insights to policymakers regarding traveler mobility and road congestion, enabling testing of various policy options.

Results indicates a significant increase in overall car travel in the modelled scenarios, which in New York City primarily means a shift away from transit. Aside from implications for MTA's revenue, this suggests that even if automated driving systems lead to a lower dollar-value fare on a shared mobility service, there may be increases in the time cost of a trip, as vehicle congestion is likely to rise. Fare and vehicle speed are currently exogenous; a worthwhile extension to the model would be to endogenize both the dynamics of changes in fare as a result of lengthening trip times, as well as the impact of such changes on supply and on demand. This could be accomplished by making total vehicle miles traveled, on an hourly and zone basis, endogenous to the model in the form of a congestion term. The congestion term would affect the price of adding capacity, as well as wait time, travel time, and fare. Such a model would both more completely reflect how the utility of a TNC trip changes when demand is high, and how demand reacts in turn.

The model requires vendors to earn revenue by providing trips. Another extension to the model would be to more fully represent the ways that vendors can replenish their stock of cash on hand, such as by turning to venture capital funding.

A model with the above-mentioned enhancements – both a more complete representation of utility, as well as vendor financing – would also highlight one of the model's existing contributions: it represents competition among vendors for a limited regional pool of trip capacity, with a price that increases as supply runs short.

The calibration approach taken in and of itself represents a research contribution. The use of zone-by-zone trip imbalances to calculate the level of empty repositioning trips, and thus the minimum TNC fleet size active at any given hour of the day, represents a practical workaround for one of the recognized challenges of working with NYC's public TNC data, which is rich in trip-related characteristics but poor in details about the fleet supplying the trips.

Additionally, this work demonstrates how SD and agent-based models can complement each other, and in particular, the value of pairing a fast, easy-to-run SD model with a downstream agent-based model that takes more details into account but is much more time-intensive to run. Calibrating the SD model with real data allows it to provide initial fleet estimates to POLARIS. In turn, the agent-based simulation performed by POLARIS can provide updated wait times, mode shares, empty miles and loaded miles, which can be used to fill a current gap in models that treat transportation supply as fixed. Linking the SD model to POLARIS allows the more-detailed model to benefit from the endogeneity of the SD model.

Appendix – Detailed model description

Model inputs for the two initial vendors, i and j, are listed below in Table 2. Some variables have an array of values, one for each shared mobility service vendor; for these, initial values are shown for i and then for j.

Table 2 Model inputs (working clockwise around the diagram)

Exogenous inputs	Initial Value	Units	Comment
trip adjustment time	1	months	Asserted, used to regulate how fast trips for a vendor go up or down
v	28,28	$/ trip	Variable cost to the vendor per trip. Driver pay per trip (including 15% tip) is $21
f	2.7, 2.7	$ / (trip / month)	Asserted; fixed cost to the vendor which scales with vendor capacity. For example, if the vendor has a capacity of 10,000 trips / month, and f = 2.7, then the fixed cost is $27,000 / month.
Initial cash on hand	$50M, $20M	$	
capacity adjustment time	1	Month	Asserted; used to regulate how fast vendor capacity can change.
Reference capacity	15M	Trips / month	Used to scale the variation in spot price
Monthly wear-out fraction	0.05	Dimensionless	Fraction of unused regional capacity that wears out each month
System maximum price	5	$/(Trip/Month)	Maximum for spot price
Create capacity parameter	2M	Dimensionless	Scaling parameter to indicate how fast new capacity can be created
Capacity rebuild time	0.5	Month	Time constant for rebuilding the pool of unused regional capacity
information from other vendors	0		Placeholder for variable representing the degree to which vendors have information from or about other vendors, to inform the desire to increase capacity
target utilization (rho)	0.7, 0.7	dimensionless	Asserted. May vary by vendor. This is the desired fraction of time a shared vehicle is serving travelers. It includes both the time that vehicles are repositioning themselves, empty, to pick up a traveler, and time with the traveler(s) on-board.

Exogenous inputs	Initial Value	Units	Comment
vendor's initial capacity	21M, 7M	Trips / month	Asserted: trips / month for each vendor. Capacity of 0 will lead to a floating point (divide by 0) error
r	0.5,0.5	minutes	Wait time parameter that varies with vendor utilization. This drives about 3 minutes of wait time at 0.667 utilization
d	60,60	minutes/hr	Wait time parameter that varies with vendor capacity (represents empty travel time for a nearby vehicle)
c	3,3	minutes	Minimum wait time. Based on regression with actual wait times
Vehicle speed	15	Mi / hr	Used in calculation of wait time
Region area	300	Mi*mi	Area of the region
Working hour per month	300	Hr	
fare	38,38	$	Fare for each vendor. Taken from NYC data
value-of-time	15	$ / hour	Asserted, used to relate fare and wait time in the utility equation
asc	0.79, 0.36		Alternative specific constant, adjusted to match modeled mode shares with those from POLARIS, or from observed data
wait time coefficient	-0.05		Wait time coefficient for the logit model
theta θ	0.39		Logsum parameter (should be between 0 and 1). This value taken from POLARIS.
asc s	-1		Alternative specific constant, for all of the shared mobility services, adjusted to make modeled mode shares roughly match those in New York
utility a	0.8		Utility for other modes
utility n	-0.45		Utility for no travel (used to model induced trips)
total trips	500M	Trips / month	Trips in the region to be served by the vendors

The equation for vendor's total operating cost ($ / month) is

$$total\ operating\ cost = f * vendor\ capacity + v * trips\ using\ vendor$$

The equation for utilization (dimensionless) is

$$utilization = \frac{trips\ using\ vendor}{vendor\ capacity}$$

The equation for wait time (minutes) is

$$wait\ time = c + \frac{d}{vehicle\ speed\sqrt{vendor\ capy\ per\ sq\ mi}} + \min\left(120, \frac{r}{1 - \ utilization}\right)$$

Its three components are

- c, a constant, in minutes;
- d, set to 60 minutes / hour. Represents empty travel time.
- r, a parameter to represent the wait time for the next available vendor, which is inversely proportional to 1 - utilization.

Within the lower level nest (shared mobility vendors competing with each other), the equation for utility is

$$utility = wait\ time\ coefficient\left(fare + \frac{value\ of\ time}{60\ min/hr} * wait\ time\right) + asc$$

The equation for sum of utilities is

$utilitysum = \sum_{vendors} \exp(utility[vendorID]\ /\theta)$ and $logsum\_s = \ln\ (utilitysum)$

The equation for vendor mode share within the lower level nest is

$$mode\ share[vendorID] = \frac{\exp(utility[vendorID]/\theta)}{utilitysum}$$

Moving to the higher-level nest, the combined utility for the shared mobility services is

$$utility\ s = \theta logsum\ s + asc\ s$$

The equations for sum of utilities and mode shares are as expected, where x represents the three upper level modes: shared service, all other, no travel (s, a, n).

$$utilitysum\ all = \sum_{x=\ s,a,n} \exp(utility[x])$$

$$mode\ share(x) = \exp(utility[x])\ /utilitysum\_all$$

Desired trips for each vendor is

$$desired\ trips\ for\ vendor = total\ trips * mode\ share\ s * mode\ share\ nest$$

Total trips is the universe of possible trips, including potential new trips via induced travel.

The equation for vendor capacity increase (trips / month) is

$$vendor \max\ capacity\ increase = \max\left(0, \frac{vendor's\ cash\ on\ hand}{per\ unit\ cost\ to\ increase\ capacity}\right)$$

The equation for vendor target capacity (trips / month) is

$$vendor\ target\ capacity = \frac{trips\ using\ vendor}{target\ utilization}$$

The equation for spot price is

$$spot\ price = system\ maximum\ price * \exp\left(\frac{-unused\ regional\ capacity}{reference\ capacity}\right)$$

Figure 5 Spot price (reference capacity=15000, system maximum price=5)

Creation of new capacity has a simple linear relationship with spot price and unused regional capacity

$$\begin{aligned} &create\ new\ capacity \\ &\quad = create\ capy\ parameter \\ &\quad * unused\ regional\ capy\left(\frac{spot\ price \big/ system\ maximum\ price}{capy\ rebuild\ time}\right) \end{aligned}$$

The equation for actual capacity increase for each vendor is

$$\begin{aligned} &actual\ capacity\ increase \\ &\quad = \left(\mathrm{MaxAffordable}\left(1 - a \exp\left(\frac{-interim\ capy}{1 + \mathrm{MaxAffordable}}\right)\right)\right) / capacity\_adjustment\_time \end{aligned}$$

Where

- a is an exponent modifier for testing, now set to 1.
- Interim capy is based on unused regional stock and the vendors desired capacity increase

$$Interim\ capy(vendor) = UnusedRegionalCapy(1 - \exp\left(-\frac{desired\ capy\ increase(vendor)}{1 + UnusedRegionalCapy}\right))$$

Acknowledgment

This paper and the work described were sponsored in part by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the NetZero project, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The following DOE manager played important roles in establishing the project concept, advancing implementation, and providing ongoing guidance: Erin Boyd. The submitted manuscript has been created by its authors and by the UChicago Argonne, LLC, Operator of Argonne National Laboratory (Argonne). Argonne, a U.S. Department of Energy Office of Science laboratory, is operated under Contract No. DE-AC02-06CH11357. The U.S. Government retains for itself, and others acting on its behalf, a paid-up nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government.

The U.S. Department of Transportation's Intelligent Transportation Systems Joint Program Office sponsored final preparation of this manuscript for the 2025 International System Dynamics Conference.

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References

Erhardt, Gregory D., Sneha Roy, Drew Cooper, Bhargava Sana, Mei Chen, and Joe Castiglione. 2019. "Do Transportation Network Companies Decrease or Increase Congestion?" *Science Advances* 5 (5): eaau2670. https://doi.org/10.1126/sciadv.aau2670.

Guo, Xiaotong, Andreas Haupt, Hai Wang, Rida Qadri, and Jinhua Zhao. 2023. "Understanding Multi-Homing and Switching by Platform Drivers." Transportation Research Part C: Emerging Technologies 154 (September):104233. https://doi.org/10.1016/j.trc.2023.104233.

Harper, Corey D., Chris T. Hendrickson, Sonia Mangones, and Constantine Samaras. 2016. "Estimating Potential Increases in Travel with Autonomous Vehicles for the Non-Driving, Elderly and People with Travel-Restrictive Medical Conditions." *Transportation Research Part C: Emerging Technologies* 72 (November): 1–9. https://doi.org/10.1016/j.trc.2016.09.003.

Huang, Wentao, Yanyan Ding, and Sisi Jian. 2024. "Strategic Coopetition among Transportation Service Providers Considering Supply–Demand Congestion Effects and Asymmetric Bargaining Power." Transportation Research Part B: Methodological 188 (October):103043. https://doi.org/10.1016/j.trb.2024.103043.

Jiang, Zhoutong, and Yanfeng Ouyang. 2022. "Pricing and Resource Allocation under Competition in a Docked Bike-Sharing Market." Transportation Research Part C: Emerging Technologies 143 (October):103833. https://doi.org/10.1016/j.trc.2022.103833.

Larson, Richard, and Amedeo Odoni. 1981. *Urban Operations Research*. Prentice Hall.

Martin, Layla. 2022. "Rebalancing in Shared Mobility Systems – Competition, Feature-Based Mode Selection and Technology Choice." In Operations Research Proceedings 2021, edited by Norbert Trautmann and Mario Gnägi, 33–38. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-08623-6_6.

Martin, Layla. 2022. "Rebalancing in Shared Mobility Systems – Competition, Feature-Based Mode Selection and Technology Choice." In Operations Research Proceedings 2021, edited by Norbert Trautmann and Mario Gnägi, 33–38. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-08623-6_6.

New York City citywide mobility survey (2022) https://data.cityofnewyork.us/browse?Data-Collection_Data-Collection=Citywide+Mobility+Survey&tags=2022&sortBy=relevance&pageSize=20

NYC Taxi and Limousine Commission and DOT. 2019. "Improving Efficiency and Managing Growth in New York's For Hire Vehicle Sector."

Pandey, Venktesh, Julien Monteil, Claudio Gambella, and Andrea Simonetto. 2019. "On the Needs for MaaS Platforms to Handle Competition in Ridesharing Mobility." Transportation Research Part C: Emerging Technologies 108 (November):269–88. https://doi.org/10.1016/j.trc.2019.09.021.

Ruutu, Sampsa, Thomas Casey, and Ville Kotovirta. 2017. "Development and Competition of Digital Service Platforms: A System Dynamics Approach." Technological Forecasting and Social Change 117 (April):119–30. https://doi.org/10.1016/j.techfore.2016.12.011.

Stephens, T.S., J. Gonder, Y. Chen, Z. Lin, and C. Liu. 2016. "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles." Technical Report: NREL/TP-5400-67216. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy17osti/67216.pdf.

Wang, Senlei, Gonçalo Homem de Almeida Correia, and Hai Xiang Lin. 2022. “Modeling the Competition between Multiple Automated Mobility On-Demand Operators: An Agent-Based Approach.” Physica A: Statistical Mechanics and Its Applications 605 (November):128033. https://doi.org/10.1016/j.physa.2022.128033.

Wong, R. C. P., Jintao Ke, W. Y. Szeto, and P. L. Mak. 2024. “Multiple Shared Mobility Services under Competition: Empirical Evidence for Public Acceptance and Policy Insights to Sustainable Transport.” International Journal of Sustainable Transportation, July. https://www.tandfonline.com/doi/abs/10.1080/15568318.2024.2384613.