RIDE-HAILING FARES AND DEMAND INTERACTIONS: INSIGHTS FROM MARKET ANALYSIS OVER SPACE AND TIME

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Research in Transportation Economics, Vol. 116, 101738, March 2026.

ABSTRACT

Ride-hailing providers like Uber, Lyft, and Didi compete daily in global markets, yet existing research has largely overlooked the dynamic interdependence between fares and demand across time, location, and service providers. This study addresses that gap by jointly estimating the simultaneous relationship between demand and per-mile fares for Uber and Lyft in New York City (NYC). A system of simultaneous equations is solved using instrumental variables that account for cross-equation correlation and endogeneity. The analysis leverages operator-specific fare data and served-trip demand every 10 minutes over a 15-day period across NYC's 260 taxi zones. Weather variables (precipitation, temperature, wind speed) are used as instrumental variables to identify exogenous shifts in demand. A multiway-clustered variance estimator reflects heteroskedasticity plus correlations across time and space, and multiway block bootstrapping captures cross-cluster correlations. Model estimates suggest that a $1-per-mile rise in Uber's and Lyft's fares will lower the demand (trip requests) by 5.8% and 64%, and a 1 SD rise in precipitation (3.35 inches) lowers demand by 17%. A 1 SD rise in temperature and wind speed (6.1°F and 2.8 mph) raises demand by 4.4% and 3.7%, respectively. The cross-equation effects suggest that a 1 SD rise in demand results in a 9% rise in Uber's per-mile fares but just 2.2% in Lyft's fares.

Keywords: ride-hailing services, market competition, supply and demand, TNCs, demand prediction, pricing strategies.

BACKGROUND

On-demand ride-hailing services are transforming urban travel patterns by facilitating efficient matching between drivers and passengers through smartphone apps (Wang et al., 2016; Chen et al., 2020; Ke et al., 2020; Zhou et al., 2022a and Zhou et al., 2022b). These apps collect real-time data from passengers and drivers, giving them control over short-term supply and demand. On the demand side, surge pricing, which varies based on time and location, influences passengers' choice of provider (e.g., Uber or Lyft, DiDi or ApolloGo). On the supply side, providers adjust surge pricing and vehicle dispatching strategies to manage the availability of vehicles throughout the day (Chen et al., 2020). Ride-hailing apps are popular not just because of their convenience and technology but also due to their pricing strategies. To draw in more users, many of these apps give subsidies to both passengers and drivers (Wang et. al., 2016). It is also common for these providers to strategize their fares and services to capture a larger market share while competing in local markets. For instance, Didi and Uber China were in a price war until 2016, but by November 2023, Uber regained a portion of its lost market share, stabilizing competitive dynamics between the two companies. Didi also faces competition from Chinese rivals, like Shouqi, Meituan, and Shenzhou (Zhou et al., 2022a). Currently, Uber and Lyft compete in the U.S., while Grab and Gojek compete in Southeast Asia, Ola and Uber in India, Bolt and Uber in Europe, and Careem and Uber in the Middle East (Wang and Yang, 2019).

Paronda et al. (2016) analyzed Uber, conventional taxis, and GrabCar in the Philippines, finding that Uber's service was 75% faster than its competitors and 35% and 28% cheaper than GrabCar and taxis, respectively. Their findings also revealed that GrabCar was the most reliable for vehicle availability, while Uber received the highest service-quality ratings. But they did not consider the role of drivers as a third party in the competition. Some of these limitations were later addressed by Huang et al. (2023), who analyzed spatiotemporal variations in ride-hailing fares and driver behavior characteristics to assess the social welfare of passengers and drivers. They also evaluated market share and competition intensity to capture the competitive dynamics among four operators in New York City (NYC): Uber, Lyft, Juno, and Via. The results showed that competition was most intense during weekday morning rush hours (6 to 8 a.m.), significantly higher than on weekends. This study highlighted that greater competition intensity lowers passenger costs and raises driver income, although excessive competition reduces the profitability of ride-hailing operators. Similarly, Meskar et al. (2023) investigated spatiotemporal pricing, driver compensation, and matching rates on a dynamic fleet-based ride-hailing operator aimed at maximizing profits. Their study considered drivers' possibility to accept or decline ride requests and showed that networks with balanced demand patterns were the most profitable. They concluded that the more balanced the demand across the network, the higher the potential profit for the operator. But neither of these studies allowed for feedbacks between provider fares and (instantaneous) service demands.

A few studies have emphasized the effects of pricing dynamics on operator revenue in a competitive market (Chen et al., 2023; Huang, 2023). Rather than directly using the intractable stochastic dynamic program to balance spatial–temporal mismatches between passenger demand and driver supply, Chen et al., 2023 proposed a deterministic convex program (DCP) that captures the trade-off between pricing revenue and vehicle availability across regions and time. Their findings showed that dynamic pricing adjusted to local shortages and surpluses when tested on NYC market, yielded 5–6% higher revenue and served 3–4% more passengers versus a best-available static schedule. Huang (2023) focused on fare strategy modelling using machine learning methods. He predicted NYC taxi fares using trip distance (computed via the Haversine formula) and passenger count, comparing linear regression, decision tree, and random forest models. As expected, all three achieved reasonably low error; the two tree-based methods gave more accurate results than ordinary least squares. The linear regression model yielded an RMSE of 1.718, a decision tree cut that reduced the error by roughly 26% down to 1.277, and the random forest improved accuracy further with an RMSE of 1.264, an additional 1% improvement over the decision tree alone.

Fare-setting strategies under competition are not limited to ride-hailing markets. Airlines too adjust fares to capture the market and optimize profits across millions of OD pairs and departure times. Paithankar et al. (2024) analyzed seasonality, cabin type, and other features affecting US-carrier airline fares using feasible generalized least square regression. They found that international trips from the U.S. between October and December are more expensive than those in June, and business-class tickets cost nearly five times more expensive than economy-class tickets. While these studies shed light on pricing strategies, they fail to account for simultaneity between fares and demand levels, by day of year, departure time, and OD pair. In reality, fare adjustments influence demand, and demand fluctuations, in turn, affect fares, creating an endogeneity issue that requires a more robust estimation to capture these interdependencies effectively.

This simultaneity issue has been partially addressed by Parvez et al. (2023), who analyzed both the continuous decision of trip fare and the discrete destination choice of TNC users. They modeled fare with a linear regression (LR) whose right-hand side includes trip attributes (distance, peak-period indicators, shared-ride flag), origin and destination activity measures (recent demand, distance to CBD), built-environment and weather covariates, plus a term for unobserved factors shared with destination choice. Destination choice was predicted by a multinomial logit (MNL) over 30 census-tract alternatives, with utilities that depend on origin–destination distance, land-use mix, infrastructure (bus stops, bike lanes, transit score), demographics, and the same latent factor in the LR. Their results showed that the joint LR-MNL model outperformed separate fare and destination models: the joint system achieves a higher log-likelihood (LL = 222,717 vs. 222,858 for the independent models) and a lower Bayesian information criterion (BIC = 45,793.20 vs. 46,075.04). In the fare equation, trip distance was the strongest positive driver of cost, peak-period trips carried a significant surcharge, shared trips had lower fares, and both built-environment (e.g., distance from CBD, nearby transit stations) and weather (snow depth) showed measurable influence on fares. In the destination choice model, longer OD distances and residential or institutional land uses suppressed choice probability, while commercial/recreational areas, higher transit and walk scores, and street density attracted more trips. All else equal, rides that begin farther from the central business district had higher fares, presumably due to drivers covering longer empty distances (dead heading") to pick up riders located far from other trip-makers, resulting in more empty miles (as discussed in Gurumurthy et al., 2021, for example).

Related to this, Özkan (2020) derived structural insights into when simple "charge-everyone-the-same" fares and "serve-only-local" matches suffice. He also identified when operators must optimize both origin-specific pricing and cross-zone matching (subject to supply) demand flow conservation and the requirement that drivers earn the same per-unit-time revenue in every location, to outperform one-size-fits-all policies. He showed that, under realistic heterogeneity in willingness to pay, the joint "origin-based pricing + cross-matching" scheme can raise total match rates by up to 60% over price-only or match-only baselines, even when accounting for dead-heading costs, whereas in the special case of uniform valuations simple constant fares and local matching are already optimal. Unlike Özkan (2020), Dey et al. (2021) did a data-driven, city-wide analysis of NYC's taxi market by jointly modeling two linked phenomena: the total number of monthly trips originating (from January 2015 to December 2018) in each of the city's 259 taxi zones, and the proportion of those trips served by Yellow taxis, Green taxis, or TNCs (Uber/Lyft/Juno/Via). They fit a joint econometric system made up of a negative-binomial count model for total trips and a multinomial fractional-split model for service shares, linked through shared latent-factor terms and estimated via simulated maximum likelihood using scrambled Halton sequences. Their results reveal that ride-hailing demand more than doubled over the study period—TNCs grew from 13% to 70% of all dispatches by late 2018—while traditional taxi volumes fell sharply. In the demand model, zones with higher job density, more zero-car households, and greater transit access saw the largest increases in trip counts, whereas snow depth and dense bike-lane networks reduced ride-hailing use. In the share model, higher population and median-income areas tended to favor yellow taxis, while zones farther from airports and with lower transit access shifted toward TNCs; zero-car households also raised both Green-taxi and TNC shares. A positive correlation term confirms that unobserved factors boosting the Yellow-taxi share also tend to boost the TNC share.

Although most prior studies overlook distinctions by vehicle type, a few have examined service-specific attributes and pricing. For instance, Schwieterman (2019) conducted a paired-trip analysis of Lyft, Lyft Line, UberX, UberPool, and Chicago Transit Authority (CTA) services in Chicago andfound that ride-hailing fares cost between $42 and $108 per hour of travel-time saved, far above the $14.95 per hour value of time for personal travel recommended by the U.S. DOT (UDOT 2016, in 2018 dollars). However, when accounting for business travelers, whose time is valued at $28.85 per hour under the same guidance, and for trips between neighborhoods with poor transit coverage, ride-hailing often remains a cost-effective alternative. Meanwhile, Chao (2019) took a more focused approach and analyzed UberX's surge pricing, which adjusts fares in real-time based on demand, supply, and other external conditions. He used real-time operational data from Uber's APIs for ten different origin-destination pairs, and controlled for weather (thunderstorms, squalls, mist/clouds), time of day, and day of the week. However, Schweiterman (2019) and Chao (2019) did not control for or discuss competition between providers. This gap is important to address, since competition can dramatically affect total demand, mode splits, provider profits, and traveler welfare. Demand fluctuates across time and space, as a function of trip type, land uses, traveler wealth, impatience, and so on. For example, passengers from higher-income residential areas are more willing to pay for shorter wait times and more luxurious vehicles. As a result, competition may vary greatly across different parts of a city and region, depending on the availability and popularity of ride-hailing services by neighborhood and time of year.

Several studies highlight demographic and built environment impacts on taxi demand (and, to some extent, supply). McNally and Rafiq (2021) identified population and employment as key factors, while Qian and Ukkusuri (2015) linked lower income neighborhoods to fewer NYC taxi trips. Yu & Peng (2019) emphasized the effects of the built environment on ride-sourcing. Spatial imbalances dominate taxi demand, with 90% of trips concentrated in Manhattan (Qian and Ukkusuri, 2015), district-level disparities in Munich (Jager et al., 2016), and local imbalances in Shanghai (Liu et al., 2012). Geographically Weighted Regression (GWR) models (Chen et al., 2021; Li et al., 2019) address spatial heterogeneity; however, spatial spillover effects, or interactions between neighboring areas, remain underexplored. While studies including Correa et al. (2017), Pan et al. (2019), and Lavieri et al. (2018) employed spatial error/lag models or multivariate count models, none fully address spatial autocorrelation in explanatory variables or quantify spillover effects. Temporally, demand fluctuates daily (Zhu and Mo, 2022; Liu et al., 2015) and weekly (Zhao et al., 2016), with time series (Moreira-Matias et al., 2013) and machine learning (Zhou et al., 2019a) aiding prediction. This study bridges existing gaps by jointly estimating ride-hailing demand and corresponding fares while accounting for spatial and temporal spillover effects.

This gap is important to address for dense urban areas like NYC, where competition among ride-hailing operators is influenced not only by spatiotemporal variations but also by regulatory policies and consumer preferences. In January 2025, the New York State government started a $1.50 congestion charge to be added to Uber and Lyft fares for trips entering Manhattan south of East 60th Street, which is passed on to riders (Congestion Pricing Program 2024). This charge is in addition to the existing For-Hire Vehicle Congestion Surcharge of $2.75, which applies to all ride-hailing trips that both begin and end in New York State and either begin, end, or pass-through Manhattan south of, but not including, 96th Street (Congestion Surcharge, 2024). These fare updates have influenced the demand for Manhattan ride-hailed trips, and probably also their fares, as consumers may shift among service options available to reduce costs or avoid premium services. This dynamic disequilibrium affects the competitiveness and pricing strategies of ride-hailing providers, and this study examines the interdependence between fare and demand across NYC operators.

This study extends previous research (Zheng et al., 2022; Zhu et al., 2022) by modeling competitive fare interactions between two dominant ride-hailing operators while incorporating spatiotemporal spillover effects that influence pricing strategies across urban regions and endogeneity between fare and demand. It advances the understanding of fare and demand variation among ride-hailing operators using a three-stage least square (IV3SLS) estimation approach to analyze Uber and Lyft trips in NYC. It sheds light on how fare strategies diverge across operators, neighborhoods, and times of day by integrating trip data with demographic, weather, and built environment variables. The following section outlines the datasets used in this study, followed by a description of the methodology employed. The last two sections present model estimates, and a summary of findings.

DATA DESCRIPTION

This paper leverages detailed ride-hailing trip data from NYC (TLC Trip Record Data, 2024) across all five boroughs (Bronx, Brooklyn, Manhattan, Queens, and Staten Island) and Newark Airport. The full dataset includes trip records from medallion-regulated yellow and green taxis alongside app-based for-hire services; however, our analysis is confined to the Uber and Lyft subsets, comprising approximately 9.8 million rides between September 15 and September 30, 2024. These trips represent roughly 65–70% of the total for-hire vehicle market in New York City (NYC TLC, 2024). The dataset contains pickup (trip start) and end times (to the second), origins and destinations (to the level of 260 taxi zones), network distance traveled per trip (in tenths of miles), whether the ride was requested as a shared ride, and whether a match was made. It includes details on the base fare and any additional fees, such as, tolls, surcharges, and airport fees. These zones collectively span over 306 square miles, covering the primary regions Uber and Lyft serve. Table 1 provides summary statistics of all variables available in this dataset. Uber dominates NYC's ride-hailing market, with approximately 72% of all trips analyzed (compared to Lyft's

28%). The ride-sharing requests are relatively low, with only about 3.07% of all trips involving riders requesting this service and an even smaller fraction (0.99%) resulting in a matched ride.

TABLE 1 Summary Statistics of NYC's Uber + Lyft Trips from September 15 to 30, 2024
(n = 9,875,667 ride-hailed trips)

Variable Name	Mean	Std. Dev	Min	Median (50%)	Max
Trip Distance (miles)	2.87 mi	5.93	0.00	2.21	10.9
Trip Duration (minutes)	18.4 min	10.98	0.00	15.8	52.1
Passenger Wait Time per Trip (min)	4.66 min	2.24	0.00	4.25	11.3
Fare Paid per Trip ($)	$16.19	7.32	0.00	14.5	43.6
Fare per mile-Uber ($ per mile)	$6.35	2.60	0.03	6.10	15.6
Fare per mile- Lyft ($ per mile)	$8.07	3.03	0.01	6.50	15.6
Tolls Paid per Trip ($)	$0.72	2.65	0.00	0.00	66.6
Black Car Fund per Trip ($)	$0.46	0.22	0.00	0.42	1.16
Sales per Tax per Trip ($)	$1.43	0.65	0.00	1.28	3.43
Congestion Surcharge per Trip ($)	$0.93	1.30	0.00	0.00	5.50
Airport Fee per Trip ($)	$0.19	0.67	0.00	0.00	7.50
Tips Paid per Trip ($)	$1.01	2.72	0.00	0.00	100
Driver's Pay per Trip ($)	$13.7	6.18	0.00	11.3	30.9
Monday Trips (Indicator)	0.12	0.32	0.00	0.00	1.00
Tuesday Trips (Indicator)	0.12	0.32	0.00	0.00	1.00
Wednesday Trips (Indicator)	0.12	0.33	0.00	0.00	1.00
Thursday Trips (Indicator)	0.13	0.34	0.00	0.00	1.00
Friday Trips (Indicator)	0.21	0.41	0.00	0.00	1.00
Saturday Trips (Indicator)	0.17	0.37	0.00	0.00	1.00
Sunday Trips (Indicator)	0.14	0.34	0.00	0.00	1.00

The demographic data for the OD zones were obtained from EPA's Smart Location Data (NYC Planning, 2024). In a competitive ride-hailing market, fare, destination, and trip distance all affect demand (i.e., the number of ride requests), and demand can also influence fares. Daily weather conditions were included in the analysis by retrieving daily meteorological data from Meteostat (2023), at the weather station nearest Manhattan (40.7128° N, –74.0060° W). This data includes average temperature, total precipitation, and average wind speed for each calendar day. These variables were then merged with the ride-hailing records by date, ensuring that each 10-minute fare bin in a given zone was associated with the corresponding daily weather conditions. During peak periods, a surge in trip requests might lead to surge pricing, which raises fares. This surge in demand may also lead to congestion, resulting in longer trip durations. To analyze the interdependence between demand, supply, and fares, trips were grouped into 10-minute bins (over 15 days and 24 hours) for each of the 260 zones, capturing short-term demand fluctuations. Of a potential 561,600 bins (260 zones × 15 days × 24 hours × 6 bins per hour), 495,128 bins exist in the dataset.

TABLE 2 Summary Statistics of Trip, Demographic, Built-Environment, and Weather Variables Within Spatiotemporal Bins (N = 495,128)

	Model Variables	**Mean**	**Median**	**Std Dev**	**Min**	**Max**
Trip Variables	Demand (Trips Served within bin)	308.4	239.5	253.8	2.0	2064
	Uber's Fare ($ per mile within bin)	6.24	6.19	1.09	2.70	11.84
	Lyft's Fare ($ per mile within bin in zone)	6.09	5.65	2.42	0.09	13.68
Demographic Variables	Population Density (people/acre in zone)	52.71	9.73	94.4	0.0	728.1
	Employment Density (Jobs/acre in zone)	106.9	3.53	475.1	0.0	4925
	Household Workers Per Job in Zone (Workers/Job in Zone)	0.501	0.121	0.678	0.0	3.39
	Total Road Network Density (Facility Miles of Road Links Per Square Mile in Zone)	35.87	26.07	49.07	0.0	355.5
	Street Intersection Density (Intersections/Square Mile in Zone)	182.7	72.9	278.9	0.0	1804
	# Workers Earning $1250 Per Month or Less at Pickup Zone	185.8	115.8	288.2	0.0	2407
	# Workers Earning Between $1250 To $3333 Per Month at Pickup Zone	275.7	147	456.7	0.0	4052
	# Workers Earning $3333 Per Month Or More at Pickup Zone	416.6	196	668.6	0.0	5398
	# Jobs In Zone Per Household in Pickup Zone	33.6	0.22	256.9	0.0	3034
	# Household Workers Per Job at Pickup Zone	0.49	0.12	0.68	0.0	3.40
	College/Associate Degree Holders Per Capita (Pickup Zone)	0.13	0.14	0.05	0.0	0.24
	Bachelor’s Degree Holders Per Capita (Pickup Zone)	0.16	0.15	0.09	0.0	0.48
	Professional Degree/Graduate People Per Capita (Pickup Zone)	0.13	0.09	0.1	0.0	0.40
	Married People Per Capita (Pickup Zone)	0.31	0.31	0.10	0.0	0.49
	Divorced Or Separated People Per Capita (Pickup Zone)	0.08	0.08	0.03	0.0	0.15
	Widowed People Per Capita (Pickup Zone)	0.04	0.04	0.02	0.0	0.13
Weather Variables	Daily Average Precipitation (mm)	0.307	0.00	3.41	0.0	78.9
	Daily Average Temperature (°C)	19.37	19.0	1.07	16.1	23.0
	Daily Average wind speed (mi/h)	9.204	9.20	0.94	6.7	28.5
Event Indicators	UN General Assembly Meeting (September 19–23)	0.009	0.00	0.09	0.0	1.00
	Climate Week (September 17–24)	0.032	0.00	0.18	0.0	1.00
	Global Citizen Festival (September 23)	0.001	0.00	0.031	0.0	1.00
	New York Film Festival (September 29 – October 15)	0.001	0.00	0.031	0.0	1.00

METHODOLOGY

In this competitive ride-hailing market, endogeneity arises because demand (in terms of total trips) and fares (for both Uber and Lyft) are determined simultaneously, i.e., demand depends on fares, while fares adjust in response to demand. Such simultaneity renders the ordinary least squares estimators inconsistent if the error terms are correlated with the endogenous regressors. Thus, each fare equation (Eq 2 and 3) contains demand as a right-hand side variable, yet demand is itself a function of those fares. To resolve this feedback correlation, instrumental variables are employed within a 3SLS framework (Zha et al., 2017; Feng et al., 2023). Weather variables (precipitation, temperature, and wind speed) are used as instrumental variables since they are expected to shift demand but not directly enter the fare-setting equations (apart from their effect on demand). This methodology is implemented using Python packages “linearmodels” for IV-3SLS estimation, and “meteostat” for fetching weather data. Python is used for data preprocessing, data aggregation and regression diagnostics (using scikit-learn tools and RobustScaler). The 3SLS estimator then jointly estimates three equations: for demand (Eq. 1), Uber’s per-mile fare (Eq. 2), and Lyft’s per-mile fare (Eq. 3), while allowing for correlation among the error terms. This approach mitigates bias from simultaneity and yields consistent parameter estimates.

In practice, the error terms in these equations are correlated within a particular location over time (temporal autocorrelation) or across nearby locations on the same date (spatial autocorrelation). To address these dependencies (Tang et al., 2019; Oh et al., 2020; Wang et al., 2022), this study allows for clustered and heteroskedastic standard errors. across timestamps and zones (He at al., 2019; Kelleney and Ishak, 2021; Xing et al., 2022; Zhu et al., 2023; Zhang et al., 2023). The analysis uses trip counts summed and trip fares-per-mile averaged over 10-minute intervals by zone and operator (Table 2).

$$Q_{it}^{Total} = \beta_0 + \beta_1 W_{it} + \beta_2 F_{it}^{U} + \beta_3 F_{it}^{L,res} + \sum_{j} \gamma_j X_{ij}^{EPA} + \sum_{k} \delta_k X_{ik}^{Edu,Marital\ status}$$

$$+ \sum_{m} \theta_m X_t^{\text{Weather}} + u_{it} \dots\dots\dots\dots\dots\dots\dots\dots (\text{Eq. } 1)$$

$$F_{it}^{U} = \alpha_0 + \alpha_1 Q_{it}^{\text{total}} + \alpha_2 W_{it} + \sum_{m} \phi_m X_{im}^{\text{EPA}} + \sum_{n} \psi_n X_{in}^{\text{Edu, Marital Status}} + \sum_{p} \rho_p D_t^{\text{Events}}$$

$$+ v_{it} \dots\dots\dots\dots\dots\dots\dots\dots (\text{Eq. } 2)$$

$$F_{it}^{L} = \delta_0 + \delta_1 Q_{it}^{\text{total}} + \delta_2 W_{it} + \sum_{q} \lambda_q X_{iq}^{\text{EPA}} + \sum_{r} \mu_r X_{ir}^{\text{Edu,Marital Status}} + \sum_{s} \eta_s D_t^{\text{Events}}$$

$$+ w_{it} \dots\dots\dots\dots\dots\dots\dots\dots (\text{Eq. } 3)$$

The demand equation models the total number of trips (Q_{it}^{Total}) in a pickup zone i and during a10-minute time interval t. This demand is influenced by several factors, including passenger wait times, fares, socioeconomic characteristics, and weather conditions. $\beta_1 W_{it}$ represents the effect of wait times (W_{it}) on demand. The coefficients β_2 and β_3 correspond to the effects of Uber fares $\left(F_{it}^{U}\right)$ and Lyft fare residuals ($F_{it}^{L,\text{res}}$), respectively. The equation also includes EPA demographic variables $\left(\sum_j \gamma_j X_{ij}^{EPA}\right)$, which represent pickup-zone attributes, like education levels, employment rates and household incomes. These variables help explain how socioeconomic factors in a pickup zone affect ride-sharing demand. Similarly, education and marital status variables ($\sum_k \delta_k X_{ik}^{Edu,Marital}$) capture demographic influences on demand. The weather variables $\left(\sum_m \theta_m X_t^{Weather}\right)$ such as, precipitation, average temperature, and wind speed, are included to account for temporal variations in demand caused by weather conditions. The error term (u_{it}) captures unobserved factors that affect demand which may include sudden events or localized disruptions not explicitly specified in the model.

The Uber fare equation (Eq 2) models the average Uber fare per mile $\left(F_{it}^{U}\right)$ in a pickup zone i during a 10-minute time interval t., as a function of demand, wait times, socioeconomic characteristics (of pickup zone residents), and event-specific shocks. The constant term (α_0) represents the baseline Uber fare when all other variables are zero. The term $\alpha_1 Q_{it}^{\text{total}}$ captures the relationship between total trip demand (Q_{it}^{total}) and Uber fares. Higher demand typically leads to increased fares to balance demand and supply. The term $\alpha_2 W_{it}$ accounts for the effect of wait times (W_{it}), with longer passenger wait times potentially indicating lower ride availability, which could drive up fares. The model aggregates neighborhood-specific socioeconomic factors $(\sum_m \phi_m X_{im}^{\text{FareEPA}})$, capturing employment and income levels, along with normalized education and marital status variables $\left(\sum_n \psi_n X_{in}^{\text{Edu, Marital}}\right)$. For example, areas with higher proportions of certain demographic groups might exhibit different ride-sharing pricing patterns.

Lyft's fare equation (Eq 3) similarly follows a similar structure but uses the Lyft fare residual (the portion of Lyft's fare unexplained by Uber's fare) when regressed on Uber fares to account for their correlation and effectively isolating Lyft-specific pricing effects after removing common pricing patterns shared with Uber. The Lyft's fare model includes local demand local demand (Q_{it}^{total}), and economic, demographic factors $(\sum_q \lambda_q X_{iq}^{\text{EPA}}, \sum_r \mu_r X_{ir}^{Edu,Marital})$. Event indicator variables $(\sum_p \rho_p D_t^{\text{Events}}, \sum_s \eta_s D_t^{\text{Events}})$ capture temporal shocks for both Uber and Lyft, respectively, events conferences or festivals that capture temporal shocks in demand and fares. The error term v_{it} and w_{it} account for unobserved local factors that influence each operator's fares in pickup zone i at time interval t. he variance-covariance of the errors, $\text{Var}\left(\varepsilon_{i,t}\right)$, not assumed to be independent and identically distributed. Instead, $\text{Var}\left(\varepsilon_{i,t}\right) = \Omega$ allows within-cluster correlation. For example, if errors are clustered by pickup zone i means all observations in the location i across different times t may have correlated errors and observations in different locations $i \neq j$ are taken to be uncorrelated. In this analysis, errors are clustered by a combined identifier that merges the location and timestamp, so that all observations sharing the same cluster $C(i,t)$ can show correlated errors. The cluster-robust estimator of the variance-covariance matrix for $\hat{\beta}$ is then defined as follows:

$$\widehat{\text{Var}}(\hat{\beta})_{\text{cluster}} = (\text{X}'\text{X})^{-1}\left(\sum_{c=1}^{C} \text{X}_c' \hat{\varepsilon}_c \hat{\varepsilon}_c' \text{X}_c\right)(\text{X}'\text{X})^{-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (\text{Eq. }4)$$

Where, $c = 1, \ldots, C$ indexes the clusters, X_c is the design matrix for observations in cluster c and $\hat{\varepsilon}_c$ represents the vector of residuals for that cluster. In system of equations, let w_{it} , v_{it} , u_{it} denote the unobserved error terms in the demand, Uber fare, and Lyft fare equations, respectively, for location i at time t. These error components are then stacked into a single vector as follows;

$$\varepsilon_{i,t} = \begin{pmatrix} w_{it} \\ v_{it} \\ u_{it} \end{pmatrix}$$

If $\varepsilon_{i,t}$ follows a multivariate distribution with a covariance matrix Σ, then cross-equation correlation arises whenever Σ is not diagonal. For instance, in a three-equation system, the covariance matrix $(\Sigma, \text{Eq. }5)$ allows for nonzero off-diagonal elements, indicating correlation across the demand (Q_{it}^{Total}), Uber fare (F_{it}^{U}), and Lyft fare (F_{it}^{L}) equations.

$$\Sigma = \begin{pmatrix} \sigma_{DD} & \sigma_{DU} & \sigma_{DL} \\ \sigma_{UD} & \sigma_{UU} & \sigma_{UL} \\ \sigma_{LD} & \sigma_{LU} & \sigma_{LL} \end{pmatrix} \dots\dots\dots\dots\dots\dots\dots\dots (\text{Eq. }5)$$

Where, $\sigma_{DU} = \mathrm{Cov}(w_{it}, v_{it})$, $\sigma_{DL} = \mathrm{Cov}(w_{it}, u_{it})$, $\sigma_{UL} = \mathrm{Cov}(v_{it}, u_{it})$. The diagonal elements $\sigma_{DD}, \sigma_{DD}, \sigma_{DD}$ represent the variances of the errors in each equation, and the off-diagonal elements $\sigma_{DU}, \sigma_{DL}, \sigma_{UL}$ capture the covariance between pairs of error terms. For instance, σ_{DU} measures the correlation between the demand and Uber fare equation errors.

While robust variance estimator addresses heteroskedasticity within each cluster, it does not account for cross-cluster correlations. Citywide events or regional weather patterns can induce dependencies across these clusters. For instance, shocks affecting one zone might also impact neighbouring zones or different time intervals, creating cross-cluster correlations. Hence, this study employed the multiway cluster bootstrap method, which produces a distribution of bootstrap estimates for each model parameter and captures the variability across clusters. The multiway cluster bootstrap identifies the unique clusters in both the temporal ($\mathcal{T}$) and spatial dimensions ($\mathcal{Z}$) and estimate the initial 3SLS model ($\hat{\theta}$) using the full dataset, serving as a point of reference for the bootstrap replications. In each bootstrap iteration (b), clusters are resampled with replacement separately in each dimension, randomly drawing sample of fare bins (N_T) and zones (N_Z), each of the same size as their original sets.

$$\mathcal{T}_b^* = \{t_{b,1}^*, t_{b,2}^*, \dots, t_{b,N_T}^*\}$$
$$\mathcal{Z}_b^* = \{z_{b,1}^*, z_{b,2}^*, \dots, z_{b,N_Z}^*\}$$

Where, $\mathcal{T} = \{t_1, t_2, \dots, t_{N_T}\}$ denote the set of time clusters (i.e., fare bins) and $\mathcal{Z} = \{z_1, z_2, \dots, z_{N_Z}\}$ denote the set of spatial clusters (i.e., zones), where N_T and N_Z are the number of fare bins and zones, respectively. Let, $\hat{\theta} = \{\hat{\theta}_1, \hat{\theta}_2, \dots, \hat{\theta}_p\}$ be the initial 3SLS parameter vector, with p representing the number of estimated parameters, and let $b = 1,2, \dots, B$ denote bootstrap iterations. The bootstrap sample ($\mathcal{S}_b, Eq. 6$) is then constructed by retaining only those observations i whose fare bin belongs to $\mathcal{T}_b^*$ and whose zone belongs to $\mathcal{Z}_b^*$.

$$\mathcal{S}_b = \{i \mid \text{Fare bin } (i) \in \mathcal{T}_b^* \text{ and pick-up zone } (i) \in \mathcal{Z}_b^*\} \dots\dots\dots\dots\dots\dots\dots\dots (\text{Eq. }6)$$

The 3SLS model is re-estimated on bootstrap sample $\mathcal{S}_b$, yielding a new set of parameter estimates $\hat{\theta}_b$ for that replication, producing a distribution of bootstrap estimates for each parameter. The bootstrap mean ($\bar{\theta}_j^*$) and standard deviation (SD_j^*) for each parameter θ_j is given by

$$\bar{\theta}_j^* = \frac{1}{B}\sum_{b=1}^{B} \hat{\theta}_{b,j} \text{ and } \mathrm{SD}_j^* = \sqrt{\frac{1}{B-1}\sum_{b=1}^{B} \left(\hat{\theta}_{b,j} - \bar{\theta}_j^*\right)^2}$$

RESULTS

Table 2 shows the estimated coefficients of the demand equation, all of which are statistically significant. This study further calculated practical significance, which yields a standardized measure that captures the impact of a one-standard-deviation change in a given variable on the outcome relative to the overall variability in demand. This was achieved by first generating baseline predictions using the original 3SLS model and then changing each regressor by one standard deviation while holding other variables constant. The difference between the new and baseline predicted values was computed and then standardized by dividing it by the standard deviation of the baseline predictions. The results showed that higher fares substantially reduce demand. A one-standard-deviation rise in Uber's fares is associated with a 27% reduction in demand, while the same rise in Lyft's fares leads to an 89% drop in demand. Using a $1-per-mile increment in place of a one-standard-deviation change yields a 5.8% reduction in Uber demand and a 64% reduction in Lyft demand. The substantially larger effect of the Lyft fare residual suggests that net variations in Lyft's pricing (beyond what is explained by Uber's fare) significantly reduced passenger demand. Moreover, 1 SD longer wait times (1.54 minutes) tie to a 37% reduction in demand, highlighting the strong sensitivity of consumers to delays.

Demographic factors further contribute: a one-standard-deviation increase in the number of household workers per available job in the pickup zone results in a 9% rise in demand, and denser residential areas drive a 3.6% increase in ride-hailing usage, although employment-dense zones may shift some trips to alternative modes. Several education categories showed distinct effects on ride-hailing demand. For instance, a one-standard-deviation increase in the proportion of residents with a college degree corresponds to a 31% increase in demand. In contrast, neighborhoods with a higher share of individuals holding bachelor's degrees experience a 14% decline, while those with more professional degree holders see an 11% reduction in demand. These differences likely reflect underlying disparities in income, access to alternative transportation, and preferences for convenience. Marital status influences demand as well; compared to never-married individuals, married residents exhibit approximately a 10% lower demand, whereas divorced or separated individuals and widowed individuals show modest increases of 4.4% and 3.7%, respectively.

Table 2 Demand Model Estimates (Y= Q_{it}^{Total}, N = 437K, Adj R^2 =0.613)

Variable Name	Coefficient
Passenger Wait Time (min)	-54.52
Uber's Fare ($ per mile)	-16.17
Lyft's Fare Residual (per mile)	-278.2
Population density (people/acre) at PU Zone	0.115
Employment density (jobs/acre) at PU Zone	-0.024
# Workers earning $1250 per month or less at PU Zone	-0.114
# Workers earning between $1250 to $3333 per month at PU Zone	0.036
# Workers earning $3333 per month or more at PU Zone	0.004
# Jobs in Zone per Household in Pickup Zone	-0.027
# Household Workers per Job at Pickup Zone	2.462
College/Associate Degree Holders per Capita (PU Zone)	148.4
Bachelor's Degree Holders per Capita (PU Zone)	-363.3
Professional Degree/Graduate Degree Holders per Capita (PU Zone)	-275.4
Married people per Capita (PU Zone)	-38.90
Divorced or Separated people per Capita (PU Zone)	217.2
Widowed people per Capita (PU Zone)	314.2
Daily Average Precipitation (mm)	-12.20

Daily Average Temperature (°C)	12.70
Daily Average wind speed (mi/h)	32.40

(All variables are statistically significant at $\alpha = 0.05$)

The fare equations reveal distinct operator-specific pricing dynamics. Uber's fare equation estimates (Table 3) indicate that real-time supply availability (approximated by wait times) has a positive and highly significant effect on per-mile charges. A one-standard-deviation rise in wait time () was associated with a 9.8% rise in per-mile fares. Overall market demand, as measured by the total trip count, significantly drives fare levels: a one-standard-deviation increase in demand raises Uber's per-mile fares by 9% and Lyft's fares by 2.2% (Table 3 and 4), indicating that the operator's pricing algorithm responds strongly to real-time supply-demand imbalances. Demographic and economic variables also show a strong association with ride-hailing demand. zones with a higher share of top earners experience slightly lower surge levels, possibly because these areas are better serviced or see travel patterns that mitigate peak-time shortages. Meanwhile, the job concentration shows small but significant fare increases in more employment-dense areas, potentially because commuting hotspots face more frequent or pronounced surges during rush hours. Lyft's fare estimates (Table 4) show that its pricing is less sensitive to broader market-wide demand surges than to local, real-time driver availability. The share of workers in the highest wage bracket is negatively associated with fares, and the effects differ considerably among education variables. Taxi zones with a higher concentration of high school graduates tend to have elevated fares, potentially due to peak-hour usage.

In addition to the main market-level drivers, the model includes four event-based indicators that capture temporal shocks resulting from major gatherings and festivals in September 2023. The United Nations General Assembly is associated with a slight reduction in per-mile fares, whereas Climate Week and the Global Citizen Festival led to modest rises in per-mile charges. The bootstrap approach provides a comprehensive view of the variability in the 3SLS estimates across multiple resampled spatiotemporal clusters. For the demand equation, the results show moderate variability in its parameters. For instance, the initial coefficient for wait time is –54.5, with a bootstrap mean of –58.8 and a standard deviation of 44.2, indicating moderate uncertainty in its impact on demand. Lyft fare residual showed variability too, with its original coefficient at –278, a bootstrap means of –247, and a standard deviation of 44.8. In the Uber fare equation, the impact of wait time remains relatively stable; the original coefficient of 1.14 is closely mirrored by a bootstrap mean of 1.21 and a low standard deviation of 0.12. This consistency suggests that the surge pricing effect driven by supply constraints is robust across resampled clusters. For the Lyft fare equation, similar patterns emerge. The wait time parameter is consistently estimated with an original value of 1.25 and a bootstrap mean of 1.33, with a standard deviation of 0.12, reinforcing the critical role of real-time supply in determining fare levels. Other coefficients in Lyft's fare equation, including those for demographic factors, display narrower bootstrap variances compared to some of the demand equation parameters, suggesting that Lyft's pricing is less sensitive to broader market fluctuations and more stable in response to local conditions.

Table 3 Uber's Fare Model Estimates (Y= Q_{it}^{Total}, N = 437K, Adj R^2 =0.609)

Variable Name	Coefficient
Demand (Total Trips Requests)	0.002
Passenger Wait Time (min)	1.158
employment density (jobs/acre) at PU Zone	9.69E-05
# Workers earning $1250 per month or less at PU Zone	0.001
# Workers earning between $1250 to $3333 per month at PU Zone	-0.001
# Workers earning $3333 per month or more at PU Zone	-2.65E-04
High School Graduate people per Capita (PU Zone)	1.683
College/Associates Degree Holders per Capita (PU Zone)	-0.432
Married (people per Capita (PU Zone)	0.698
Divorced or Separated people per Capita (PU Zone)	2.445
Widowed people per Capita (PU Zone)	-0.845
UN General Assembly (September 19–23)	-1.583
Climate Week (September 17–24)	0.410
Global Citizen Festival (September 23)	0.242

(Variables are statistically significant at $\alpha = 0.05$)

Table 3 Lyft's Fare Model Estimates (Y= Q_{it}^{Total}, N = 2194, Adj R^2 =0.609)

Variable Name	Coefficient
Demand (Total Trips Requests)	0.0002
Passenger Wait Time (min)	1.263
Gross employment density (jobs/acre) at PU Zone	-3.16E-05
# Workers earning $1250 per month or less at PU Zone	0.001
# Workers earning between $1250 to $3333 per month at PU Zone	-0.001
# Workers earning $3333 per month or more at PU Zone	-2.87E-04
High School Graduate people per Capita (PU Zone)	2.566
College/Associate's Degree Holders per Capita (PU Zone)	-0.409
Married people per Capita (PU Zone)	0.884
Divorced or Separated people per Capita (Pickup Zone)	3.551
Widowed people per Capita (PU Zone)	-2.881
UN General Assembly Indicator (September 19–23)	-1.643
Climate Week Indicator (September 17–24)	0.078
Global Citizen Festival Indicator (September 23)	2.124

(Variables are statistically significant at $\alpha = 0.05$)

CONCLUSIONS

Ride-hailing services like Uber and Lyft offer a dynamic alternative to traditional taxis and public transportation. Despite their growing significance, conventional models often overlook the feedback relationship between fare and demand across time, space, and competing providers. This study addressed this gap by jointly estimating the relationship between demand and per-mile fares for Uber and Lyft in New York City using a three-stage least squares (IV3SLS) system of simultaneous equations. On the demand side, the analysis showed that both fare levels and wait times are key drivers, with higher fares and longer wait times resulting in significantly fewer trip requests, especially for Lyft users, who showed higher sensitivity to fares compared to Uber users.

A dollar per mile rise in Uber's fares reduces demand by 5.8%, whereas the same increase in Lyft's residual fare leads to a 64% drop. A one standard deviation (SD) rise in wait times (1.54 minutes), too, was associated with a 37% reduction in demand, emphasizing that riders are highly susceptible to delays. These associations are additionally affected by underlying demographic and environmental conditions. The results showed that educational attainment and income levels have a differentiated impact on ride-hailing demand. Areas with more college-educated residents show a 31% increase in demand, while regions with higher proportions of bachelor's or professional degree holders experience declines.

Marital status also plays a role, with married individuals showing lower demand relative to never-married individuals, while divorced or widowed populations exhibit modest increases. Weather conditions are equally influential; rainy conditions reduce demand by 17%, whereas hotter temperatures and higher wind speeds (+6.1°F and +2.8 mph) lead to modest increases, reflecting consumers' preferences for comfort and convenience. On the fare side, both Uber and Lyft employ dynamic pricing models that respond to real-time supply constraints. The results showed that fares increased with longer wait times, reflecting the surge pricing effect triggered by limited driver availability. However, Uber's fares were observed to be more responsive to overall market demand than those of Lyft. Moreover, wealthier neighborhoods tend to experience lower surge levels, likely due to higher driver availability or less pronounced peak-hour fluctuations. In contrast, middle- and lower-income areas tend to see slightly higher fares, suggesting greater supply-demand mismatches in these regions. Although the demand estimates show only moderate variability across clusters, this moderate variability reflects local and temporal heterogeneity that significantly influences consumer behavior. For example, the effect of wait time on demand differs considerably across taxi zones and time intervals, indicating that localized congestion and regional economic conditions have a substantial impact on ride-hailing usage. In contrast, the fare equations for both Uber and Lyft display remarkably stable wait time coefficients. This stability implies that surge pricing mechanisms are robust across diverse spatiotemporal clusters, regardless of the specific pickup zone or time of day, the response to supply constraints remains consistent.

These outcomes emphasize the diverse factors influencing ride-hailing dynamics, which are systematically examined by addressing several key challenges simultaneously. It resolves simultaneity by modeling the bidirectional feedback between operator-specific fares and demand using instruments within a three-stage least squares framework. It captures spatiotemporal dependencies by including both within-cluster and cross-cluster correlations across time and space, revealing distinct pricing strategies and demand sensitivities across competitors. Future research should extend the timeframe to capture longer-term and seasonal variations, particularly under evolving regulatory regimes like new tolling policies. Further exploration into different service tiers, namely, premium or luxury options, and a deeper examination of driver-side factors, including acceptance rates and fleet size, are warranted. Exploring unobserved rider factors, like brand loyalty and past wait-time experiences, may further refine the understanding of operator preferences and lead to more adaptive fare strategy models.

ACKNOWLEDGMENTS

This article and the work described were sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The U.S. Government retains for itself, and others acting on

AUTHOR CONTRIBUTIONS

The authors confirm the contribution to the paper as follows: Conceptualization, data curation, formal analysis, investigation and methodology: Priyanka, P.; Gurumurthy, K.M; and Kockelman, K.; Project administration and Supervision: Kockelman, K. and Gurumurthy, K.M; Visualization and Writing – original draft: Priyanka, P., Kockelman, K.; Writing – review & editing: Kockelman, K. and Gurumurthy, K.M; The authors confirm their respective contributions to this manuscript as outlined above. We acknowledge and thank Aditi Bhasker for her review and valuable feedback.

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