ONLINE APPENDIX

Appendix A: Data Appendix

A.1. Google Places Data

Table 1 shows the 93 Google place classes in our dataset and the ten broad categories: Food, Religion, Health, Stores, Entertainment, Education, Finance, Government and Others, Others, Other Transport.

Clustered Category	Google Places API Class
Food	cafe, restaurant, bakery, meal delivery, meal takeaway
Religion	church, mosque, synagogue, hindu temple
Health	dentist, doctor, gym, hospital, pharmacy, physiotherapist, spa, drugstore
Store	clothing store, convenience store, department store, furniture store, hardware store, home goods store, jewelry store, liquor store, pet store, shoe store, shopping mall, book store, electronics store, bicycle store
Entertainment	amusement park, aquarium, art gallery bar, bowling alley, movie rental, movie theater, museum, nightclub, painter, park, casino, zoo, rv park
Education	library, school, university
Finance	accounting, bank ,atm
Govt and Offices	city hall, embassy, courthouse, lawyer, local government office, real estate agency, travel agency, insurance agency, moving company
Others	airport, beauty salon, campground, car dealer, car repair, car wash, electrician, establishment, fire station, funeral home, gas station, general contractor, hair care, laundry, locksmith, lodging, parking, plumber, police, post office, stadium, storage, veterinary care, natural feature car dealer, car rental, cemetery, florist
Other Transport	subway station, train station, transit station, taxi stand, light rail station

Table 1 Google count categories from Google Places API and the ten clustered classes

Table 2 shows the descriptive statistics of the Google Place category counts (i) in the entire coverage region and (ii) around shuttle stops. The average number of places around shuttle stops appears to be greater than the overall average in the city for almost all categories. This suggests that the platform chooses the locations of stops in areas with a high expected number of originating riders. It is important to control for the potential ridership at different locations, and hence, we include these variables in our analysis..

A.2. Descriptive evidence of common users for cab and shuttle

In this section, we provide descriptive evidence to show that many customers use both the on-demand cab service and the shuttle service; hence, the market is not segmented into cab-only and shuttle-only users. Since the platform uses a unique (anonymized) identifier for each customer, we can calculate the number of shuttle and cab rides the customer takes. Let $r_i^s \in \mathbb{R}$ and $r_i^c \in \mathbb{R}$ be the number of shuttle and cab rides taken by customer $i \in \{1, ..., N\}$ in our sample period. We define customer i to be a *common user* if $r_i^c > 0$ and $r_i^s > 0$. The shuttle platform has 76K unique customers, and 70% of them are common users. On average, a common user took around 18 shuttle and 10 cab rides in the sample period. Figure 1 plots the mass of common users with r^s shuttle rides (y-axis) and r^c cab rides (x-axis) in July. We see that many users take both shuttle and cab rides. Hence, the market is not segregated into shuttle-only and cab-only users.

Google Count Category	Shuttle Stops		All grids	
	Mean	S.D.	Mean	S.D.
Food	3.22	3.33	0.66	1.27
Religion	0.18	0.50	0.66	1.60
Health	3.14	3.67	2	4.07
Entertainment	0.66	1.03	0.25	0.70
Store	5.97	5.02	6.79	10.77
Finance	7.38	5.18	1.76	3.65
Govt and Offices	4.36	3.16	1.11	2.26
Education	2.74	3.18	1	1.76
Others	65.21	10.03	21.28	26.46
Other Transport	0.38	1.46	0.25	0.97
Total	93.60	15.26	35.23	45.33

Table 2 Google count statistics around shuttle stop locations and all grids in the city. N=1,022 for the stops and 5,500 for the grids

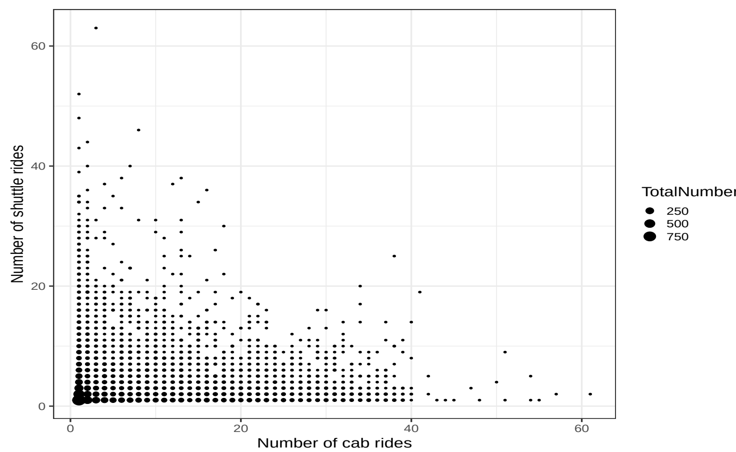

Figure 1 Number of shuttle and cab rides taken by common users in July. Size of the points denotes the number of users with (r^s, r^c) number of shuttle and cab rides.

A.3. Evidence of Substitution between Shuttles and Cabs

Given that customers take cab and shuttle rides, we first establish that the services are *substitutes* and not *complements*. They would act as complements if consumed together - for example, if customers used shuttles for the longer part of the journey and cabs as a last-mile service. However, they would act as substitutes if customers chose one service over another for the entire trip. To test whether the services are complements, we construct sequences of shuttle and cab rides taken by a customer that are sufficiently close to each other in time and space. Specifically, let t_j^s be the time of arrival (or departure) of a shuttle ride at location j and t_k^c, the time of departure (or arrival) of the cab ride from location k. We say that the two services are consumed together if, for cab and shuttle rides taken by the same customer, (a) $|t_k^c - t_j^s| < 30$ min, and (b) $d(j,k) < 1000$ m, where d is the distance operator. The percentage of such trips where the two services are consumed together accounts for less than 0.01% of the total shuttle and cab trip data, thereby indicating the lack of simultaneous consumption of the two services.

A.4. Difference-in-differences analysis

We measure substitution through a difference-in-differences analysis. We are interested in measuring the effect of introducing a new shuttle route on the cab usage on the route. We leverage the fact that the shuttle platform was adding routes as it expanded over time. Figure 2 shows the number of operational shuttle routes. The addition of routes over time is a quasi-experiment for our difference-in-differences analysis described below.

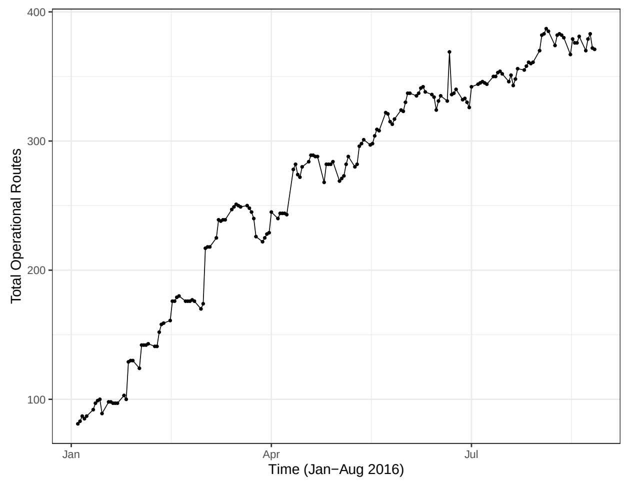

Figure 2 Number of operational shuttle routes over time (Jan-Aug 2016)

Treatment is defined as the opening of the shuttle operations on the route. Let $\mathcal{O}$ and $\mathcal{U}$ be the sets of treated and control routes, respectively. As depicted in Figure 2, there is a significant variation in the treatment timings across the treated routes from Jan-Aug 2016. Specifically, the company started shuttle operations at different times for each $o \in \mathcal{O}$. We assume that the time of the start of operations on a route is the time of the first ride we observe on route k. Let D_{rw} be the treatment indicator for route $r \in \mathcal{O} \cup \mathcal{U}$ in a weekly period $w \in \{1, 2, ...35\}$.[1] $D_{rw} = 1$ if the shuttle service was operational on route r in period w. Finally, let Y_{rw} be the number of cab rides on route r in period w. Similar to the model in (Hall and Horton 2019), we estimate the following two-way-fixed-effects (TWFE) model to identify the causal impact of opening up the shuttle route on cab ridership:

$$Y_{rw} = \alpha_r + \gamma_w + \beta_{DD} D_{rw} + g_r w + \epsilon_{rw}, \tag{1}$$

where α_r and γ_w are the route and time fixed effects; D_{rw} is the treatment dummy; β_{DD} is the average treatment effect of interest; g_r is market-specific linear trend. Before we present the estimation results, we describe the identification argument in our setting. While Ola selects the more profitable routes to introduce the shuttle service, we think it is reasonable to assume D_{rw} and ϵ_{rw} are uncorrelated conditional on the other covariates in Equation (1) for two reasons. First, our sample only includes routes where Ola operated the shuttle service at the end of the sample period. Specifically, the treated and control routes are very similar in profitability, and the differences in the unobservables are limited. Second, we include route fixed effects in Equation (1). These fixed effects absorb the remaining differences across treated and control routes. In other words, the variation we are using is the timing of the introduction of shuttle service conditional on all market-level profitability. Finally, we perform the parallel trend test to validate our diff-in-diff approach further. The results are provided at the end of this section.

Table 4 (column 1) shows the effect of the opening of shuttle services on cab usage. There is a net reduction of 84 rides per route per week when the shuttle services operate. The decline in cab ridership shows directly that the two services act as substitutes.

A.4.1. Parallel Trend Assumption We perform the parallel trend test for our diff-in-diff analysis We use a regression-based test since we have a multi-period setting with varying treatment times. Specifically, we test whether any significant time-varying differences exist between control and treatment units pre-treatment (after controlling for everything else). We run the following regression for this test:

$$Y_{rw} = \alpha_r + \gamma_w + \Sigma_{j=1}^{6} \delta_j z_{rwj} + g_r w + \epsilon_{rw}, \tag{2}$$

where the treatment indicator interacts with time dummies for pre-treatment periods. Specifically, $z_{rwj} = 1$ if week w is the jth week prior to treatment for a particular route r, and $z_{rwj} = 0$ otherwise. The parallel trend assumption states that the pre-treatment indicators are statistically insignificant. Table 3 shows the results from this exercise. All the pre-treatment indicators are statistically insignificant in our analysis, suggesting that the pre-treatment parallel trend assumption will likely hold in our setting.

	Rides	Price
δ_1	-0.356	-0.045
	(0.673)	(0.113)
δ_2	-0.424	-0.067
	(0.713)	(0.243)
δ_3	0.329	-0.024
	(0.772)	(0.386)
δ_4	-0.217	-0.043
	(0.741)	(0.143)
δ_5	0.613	-0.065
	(0.938)	(0.532)
δ_6	0.217	-0.082
	(1.112)	(0.563)
Week F.E.	Yes	Yes
Market F.E.	Yes	Yes
Linear Time trends	Yes	Yes
Observations	33,303	33,303
R^2	0.83	0.81

Table 3 Parallel trend assumption test

Appendix B: Cab supply analysis

As we do not observe driver-side information directly in the data, incorporating the supply-side estimation of the cab service in our analysis is difficult. However, the introduction of shuttle service provides an exogenous (negative) shock of demand for cab service, which allows us to estimate the supply of cabs. Below, we describe the supply estimation and then discuss the counterfactual results after incorporating the supply-side analysis. The supply side estimation also serves as direct evidence of the substitutions between cab and shuttle rides and, therefore, riders choosing between the two services.

First, since we do not observe the supply of cabs directly in the data, it is impossible to estimate a structural supply model. However, a linear approximation to the supply function is reasonable if the supply-side response is limited. We exploit the introduction of shuttle service as the "exogenous" shock to cab demand, where "exogenous" refers to demand shocks that are uncorrelated with the supply of cabs. This is a reasonable assumption in our setting for several reasons. First, our sample in this analysis includes all markets (routes) where the shuttle service was introduced during the eight-month sample period. We acknowledge that the introduction of the shuttle service is not exogenous in general–i.e., the platform selects the more profitable markets to enter. However, since we are restricting the sample to those markets where the shuttle service was introduced in this relatively short time period, we believe those markets are similar in their profitability. Second, we control for market fixed effect in all our regressions discussed in this section. In other words, the variation we are using is the timing of the introduction of shuttle service conditional on all market-level profitability. Therefore, it is reasonable to assume that the variation we exploit in the data is exogenous. Third, we perform the parallel trend test and validate our diff-in-diff approach. The details are provided in Section A.4. Finally, introducing the shuttle service affects riders' choices and, thus, the demand for cab service. In other words, this exogenous demand shock identifies and allows us to estimate the slope of the cab supply. We perform the same difference-in-differences analysis as described in the previous sections,

$$Z_{rw} = \alpha_r + \gamma_w + \beta_{DD} D_{rw} + g_r w + \epsilon_{rw}, \tag{3}$$

except we include more dependent variables. In addition to the number of cab rides on route r in week w, we include the average cab price, cab wait time, and cab travel time, all measured on route r in week w. The results are provided in Table 4.

	Cab rides	Travel Time	Wait Time	Price
β	-83.742***	-0.302*	-0.026	-5.402***
	(1.147)	. (0.122)	(0.050)	(0.673)
Week F.E.	Yes	Yes	Yes	Yes
Market F.E.	Yes	Yes	Yes	Yes
Linear Time trends	Yes	Yes	Yes	Yes
Observations	33,303	33,303	33,303	33,303
R^2	0.912	0.974	0.992	0.995

Table 4 Average treatment effect of opening of a shuttle route on market level wait, travel time and cab prices (*, **, * indicates statistical significance at 10%,5%,1% level)**

First, we find that the effect on travel time and wait time are very small in magnitude. Moreover, the effect is marginally significant for travel time and insignificant statistically for wait time. Second, we find the impact on price is statistically significant, but the magnitude is small. It suggests that the supply of cabs is relatively elastic. When the demand curve shifts downwards, the small price change relative to quantity change shows that the slope of the supply curve is small. These findings are consistent with our intuitions for two reasons. First, the flexibility of the work schedule for Ola drivers allows easy adjustment in drivers' utilization, hence the elastic supply. Second, given our shuttle routes are only a small subset of the much bigger cab market in Delhi, the introduction of the shuttle routes is unlikely to have a big impact on the overall traffic condition of the city, which ultimately determines the travel time and wait time of cab rides. In other words, although there is a significant effect on the number of cab rides in the local markets, travel time and wait time are determined by the overall congestion level, and, thus, we do not find a significant effect on them. As a result, we ignore the travel time and wait time changes in all counterfactual analyses. However, we use all counterfactuals' estimated cab supply curve for supply-side response. Since the supply-side response size is likely small, given the small slope in the diff-in-diff results, a linear function provides a reasonable approximation. The estimated slope then pins down the supply function and our data, which provides one point on the line (see Figure 3).

We calculate the congestion surcharge counterfactual, incorporating the estimated supply curve by solving the new market equilibrium after imposing the congestion surcharge. We conduct the analysis for each market and present the same results as in the main text in Figure 4. As expected, with an elastic supply curve, the results are very similar to those in the main text. We also calculate the consumer passthrough rate following the literature. We find that mean and median passthrough are above 96% across routes (see Table 5). We also calculate the commute reduction counterfactual and its implementation after incorporating the supply side. The results are very similar to those presented in the main text.

Pass Through	Mean	Min	25%ile	Median	75%ile	Max
Percentage	96.40	21.84	96.55	98.76	99.51	99.98

Table 5 Distribution of pass through rates over routes in our sample

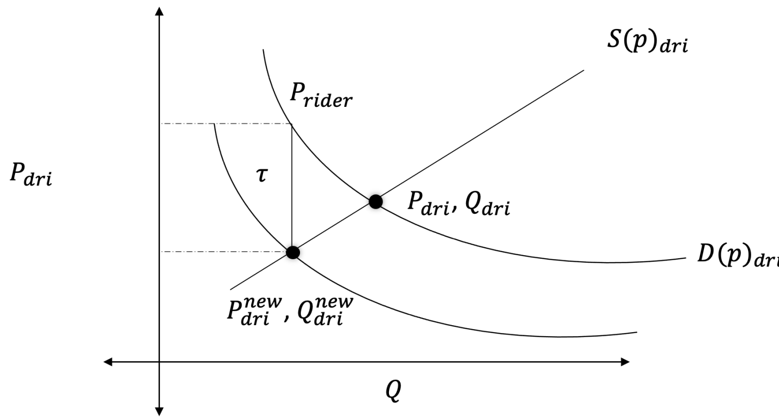

Figure 3 **Supply and demand curves and new equilibrium. The slope of the supply curve (given by the dif-in-dif analysis and the demand function pin the new equilibrium)**

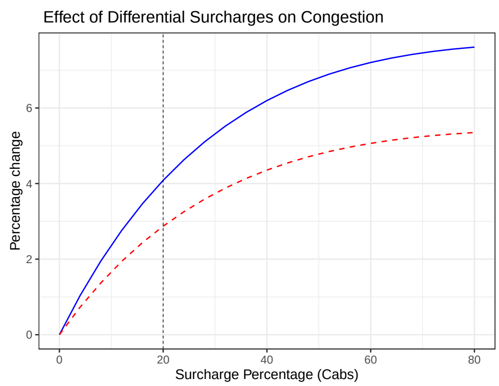

Figure 4 **Percentage reduction in number of ola vehicles due to pure substitution in morning (blue) and evening hours (dotted red line) after application of percentage surcharges. Vertical dashed line corresponds to** $\theta_c = 0.2$

Appendix C: Estimation Appendix

C.1. Market Selection and Statistics and First Stage results

To impute the characteristics of the choice that the customer does not make, we match rides spatially. In our analysis, we keep only those markets where we observe rides for both services. That is, we filter out markets without shuttle or cab rides in the eight-month sample period. This gives us 1,728 markets in total. Table 6 reports the summary statistics for the average characteristics in the matched markets across the two choices. Each variable is averaged across the matched markets. For example, the mean of the shuttle price is the average of the shuttle price calculated across all markets (where each market has an average price computed over all the rides in that market). In Table 8, we report the results from the first stage of the estimation.

C.2. Outside Good and Market Size Imputation

This section presents the imputation of the size of the outside good and, thus, the size of a market. We follow the broad guidelines outlined in Nevo (2000) to do so. The general recommendation is to have a large enough market with a non-zero share of the outside good. As in Nevo (2000), we use two key determinants for the market size: (i) a

Service	Variable	Obs.	Min	25%	Median	Mean	75 %	Max
Shuttles	Price Paid (₹)	1,728	0	30	62.41	59.92	84.23	150
	Distance (Km.)	1,728	0.3	7.7	19.5	20.93	33.4	63.9
	Time (min.)	1,728	1	24.09	47	48.95	71	132.7
	Commute (km.)	1,728	0	0.26	0.55	0.76	1.03	4.99
Cabs	Wait (min)	1,728	0.13	8.57	10.91	11.44	13.46	65.2
	Price Paid (₹)	1,728	85.56	147.96	318	330.53	455.25	1509
	Distance (Km.)	1,728	0.06	5.37	13.05	14.82	23.38	43.99
	Time (min.)	1,728	7.21	22.73	42.41	46.24	64.55	206.08
	Commute (km.)	1,728	0	0	0	0	0	0

Table 6 Summary Statistics in the Matched Data Sample

variable that is proportional to the market size and (ii) the proportionality factor. We assume that the total market size for jk is proportional to the originating traffic from j. The market size for jk can be written as :

$$\text{Market Size}_{jk} = (\text{Originating Traffic from } j) * (\text{Proportionality Factor for } jk). \tag{4}$$

The originating traffic from j is proportional to the population of j. We obtain the population density of j from the Census data. The population of the grid j is the population density multiplied by the grid area. We assume that the traffic originating j is two rides per capita per working day. This is similar to Nevo (2000), which assumes the market size of ready-to-eat cereal to be one serving per capita per day. So, our total originating traffic for eight months is the population of j * 2 * 20 * 8 (assuming 20 working days per month). We define a proportionality factor to complete the definition of the market size for jk. We use the notion of connectivity of j to k. Using our cab dataset, we find all such o with a ride from j. Let the set of all such o's be $\mathcal{N}(j)$. That is,

$$\mathcal{N}(j) := \{o \in \mathcal{N}(j) : r^c_{jo} > 0\}, \tag{5}$$

where r^c_{jo} is the number of cab rides from j to o. Our cab dataset has around two million jo pairs over the entire coverage region. Hence, we find all such o where people have traveled to from j. We count the Google places in all $o \in \mathcal{N}(j)$. Then, the proportionality factor for jk is given by:

$$\text{Proportionality Factor for } jk = \frac{\text{Google Places in k}}{\Sigma_{o\in\mathcal{N}(j)}\text{Google Places in o}}. \tag{6}$$

Figure 5 shows the set of locations in $\mathcal{N}(j)$. The incoming traffic at k is proportional to the number of Google places at k. Using this definition of market size for market jk, we calculate the number of rides for the outside good as:

$$\text{Number of rides for outside good} = \text{Market Size} - \text{Shuttle rides} - \text{Cab rides} \tag{7}$$

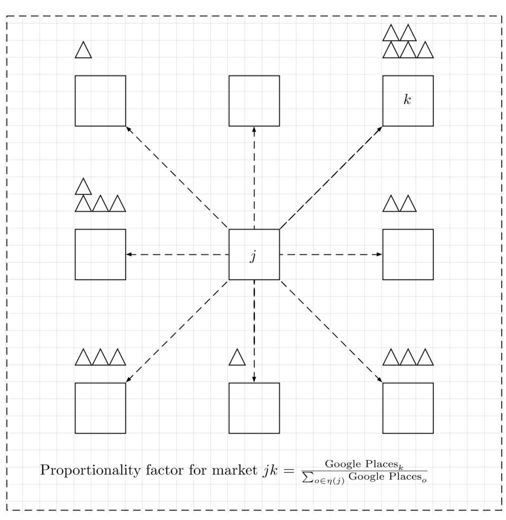

Figure 5 Proportionality factor for market jk

Table 7

	Dependent variable:		
	Shuttle Price	Cab Price	Cab Wait
	(1)	(2)	(3)
Education*Ratio(j,16,25)	14.642* (8.119)		
Health*Popden(j,16,25)	0.602*** (0.231)		
Food(k,16,25)	22.168*** (5.015)		
Education(k,16,25)	0.002* (0.001)		
TotalPlaces*Popden(k,16,20)	0.0002 (0.001)		
TotalPlaces*Ratio(k,25,25)	0.213*** (0.042)		
Others*Ratio(j,16,25)		1.352*** (0.201)	
Education*Ratio(k,16,20)		−0.001 (0.002)	
Health*Ratio(k,16,25)		1.361 (0.972)	
GovtOffice*Popden(k,16,25)		0.0003*** (0.0001)	
Others*Ratio(k,16,25)		0.705*** (0.243)	
Entertainment*Popden(k,16,25)		11.344** (4.522)	
GovtOffice*Ratio(k,16,25)		33.258* (17.152)	
Education*Workden(k,20,25)		0.002*** (0.001)	
GovtOffice*Workden(k,20,25)		−0.001 (0.004)	
Finance*Ratio(j.20,25)			0.163*** (0.029)
Others(j,16,25)			0.190*** (0.013)
OtherTransport(k,20,25)			−0.001*** (0.0001)
TotalPlaces(k,20,25)			0.0003 (0.008)
Distance.s	1.772*** (0.058)		
Commute.s	−3.246*** (0.826)		
Distance.c		16.260*** (0.273)	0.079*** (0.015)
Food.j	−0.108 (0.145)	0.229 (0.512)	−0.070** (0.029)
Religion.j	−0.788 (0.908)	−3.587 (3.213)	0.168 (0.181)
Health.j	0.804*** (0.161)	1.071** (0.534)	0.018 (0.030)
Entertainment.j	−1.676*** (0.547)	−1.056 (1.898)	−0.029 (0.107)
Store.j	0.194** (0.098)	−1.093*** (0.347)	0.013 (0.020)
Finance.j	0.294*** (0.092)	0.047 (0.324)	0.060*** (0.018)
Government_and_Offices.j	0.560*** (0.143)	−1.203** (0.507)	−0.049* (0.028)
Education.j	−1.757*** (0.193)	−4.113*** (0.661)	0.086** (0.037)
Others.j	−0.037 (0.059)	0.268 (0.207)	−0.005 (0.012)
Other_Transport.j	2.004*** (0.307)	−0.817 (1.087)	−0.225*** (0.061)
Area.j	0.004* (0.003)	0.016** (0.008)	−0.001 (0.0004)
Popden.j	−0.002** (0.001)	−0.006** (0.003)	0.0004** (0.0002)
Workden.j	0.011** (0.004)	−0.042*** (0.015)	0.001 (0.001)
Households.j	−0.007 (0.007)	0.101*** (0.025)	−0.003** (0.001)
Food.k	−0.182 (0.151)	0.474 (0.538)	−0.023 (0.030)
Religion.k	−0.656 (0.938)	−9.922*** (3.300)	0.203 (0.189)
Health.k	0.686*** (0.154)	1.915*** (0.586)	0.033 (0.033)
entertainment.k	−0.930 (0.566)	0.045 (2.006)	0.011 (0.112)
Store.k	0.217** (0.101)	−1.168*** (0.356)	−0.019 (0.020)
Finance.k	0.181** (0.089)	−1.236*** (0.315)	−0.002 (0.018)
Government_and_Offices.k	0.495*** (0.135)	−0.055 (0.480)	−0.058** (0.027)
Education.k	−1.117*** (0.189)	−0.698 (0.663)	−0.072* (0.039)
Others.k	−0.083 (0.054)	0.726*** (0.193)	−0.028** (0.011)
Other_Transport.k	1.735*** (0.308)	−2.007* (1.121)	−0.021 (0.067)
Area.k	0.012*** (0.002)	−0.038*** (0.009)	0.001* (0.0004)
Popden.k	−0.004*** (0.001)	−0.006* (0.003)	−0.0002 (0.0002)
Workden.k	0.017*** (0.005)	−0.029* (0.016)	0.001 (0.001)
Households.k	−0.009 (0.007)	0.081*** (0.025)	−0.001 (0.001)
Constant	5.817 (5.656)	14.904 (20.059)	13.218*** (1.162)
Observations	1,728	1,728	1,728
R^2	0.539	0.962	0.310
F-stats	50.91	194.32	32.57

Table 8 First-stage results for prices and cab wait. Columns one, two and three are models for shuttle price, cab price and cab wait, respectively (*,,*** indicates statistical significance at 10%,5%,1% level)**

C.3. Robustness to Alternate Specifications

In this section, we report the robustness analysis for our main set of results. We report multiple robustness results to our main specification. Specifically, we allow the parameters to vary across groups of customers based on when they adopted the shuttle service. In another robustness check, we allow preference parameters to vary by route distance. We also perform a latent class analysis to infer the customer's group assignment from the data. We estimate our model for a sub-sample where we exclude small distances to test whether our IVs are valid for short route distances. We also perform a robustness check to test an alternative way of computing the market sizes.

C.3.1. Adoption groups In this robustness check, we allow the parameters to vary by the adoption status of the customers. We define two groups - early adopters and late adopters. Early adopters are customers who took their shuttle ride in the first 60 days (Jan 1 - Mar 1); the others are classified as late adopters. The results from the analysis are reported in Table 9. Group 1 corresponds to the early adopters, and Group 2 corresponds to the late adopters. Our main results and the direction of the bias in the coefficients stay qualitatively the same. Also, we find that the early adopters are less sensitive to price, commute, and extra travel disutility than group 2 customers, which is expected due to their experience and stickiness with the platform.

C.3.2. Distance Dependent Sensitivities In this robustness check, we allow the parameters to vary by route distance. Specifically, we divide the rides into distance buckets based on the quartiles of the cab distance distribution. Group 1 represents the first quartile, and so on. We find that short-distance customers are more sensitive to price and wait times as opposed to long-distance ones. Our finding aligns with previous literature (see, for example, Rosaia (2022)). Our main results on the direction of the bias and the monetary values of the disutilities align with our main specification.

C.3.3. Latent Class Analysis We perform a latent class analysis to capture customer heterogeneity better. We let the probability that a customer belongs to a latent class be a function of the price they face. The utility function is then:

$$U_{ijkta} = X'_{ijkta}\beta_i + \epsilon_{ijkta} \tag{8}$$

where β_i is the vector of all parameters in the utility function for individual i. We allow for two latent classes. The probabilities of i belonging to class $q \in \{1, 2\}$ are given by:

$$w_{iq}(\gamma) = \frac{exp(p_i\gamma_q)}{\Sigma_{q=1}^{2} exp(p_i\gamma_q)}, \tag{9}$$

Where p_i is the monthly average price faced by i. The parameters to be estimated are $(\gamma_2, \beta_1, \beta_2)$ as γ_1 is normalized to 0. Using these probabilities, we estimate the model via maximum likelihood. The results of the exercise are shown in Table 11. The average disutilities from the model are very similar to the results of our main specification presented in the main text.

C.3.4. Sub-sample Analysis 10% of our cab trips are within 2km. We check the validity of our instrumental variables and conduct a sub-sample analysis where we only keep routes greater than 2km, measured in cab trip distance (thus filtering out the bottom 10% of the routes by cab distance). We rerun our estimation for this sample. Our results qualitatively stay the same for this subsample. This indicates that our constructed instrument variables recover the correct estimates in the sample. We include the results from this robustness check in Table 12.

Explanatory Variable	*Morning*	*Evening*
Shuttle intercept	-11.273^{***}	-14.361^{***}
	(0.144)	(0.154)
Cab intercept	-17.126^{***}	-15.261^{***}
	(0.169)	(0.174)
Price Paid 1	-0.015^{***}	-0.011^{***}
	(0.0001)	(0.0001)
Price Paid 2	-0.018^{***}	-0.016^{***}
	(0.0001)	(0.0001)
Wait 1	-0.140^{***}	-0.128^{***}
	(0.001)	(0.001)
Wait 2	-0.140^{***}	-0.127^{***}
	(0.001)	(0.001)
Frequency 1	0.426^{***}	0.394^{***}
	(0.011)	(0.012)
Frequency 2	0.473^{***}	0.421^{***}
	(0.012)	(0.013)
Time	-0.011^{***}	-0.010^{***}
	(0.0001)	(0.0001)
Commute 1	-0.989^{***}	-0.773^{***}
	(0.013)	(0.013)
Commute 2	-1.214^{***}	-1.104^{***}
	(0.015)	(0.013)
Distance 1	-0.235^{***}	-0.147^{***}
	(0.005)	(0.006)
Distance 2	-0.261^{***}	-0.155^{***}
	(0.006)	(0.007)
Controlfunction Shuttle Price	-0.025^{***}	-0.021^{***}
	(0.0001)	(0.0001)
Controlfunction Cab Price	0.006^{***}	0.007^{***}
	(0.0002)	(0.0001)
Controlfunction Cab Wait	0.071^{***}	0.085^{***}
	(0.007)	(0.008)
Controlfunction Frequency	0.063^{***}	0.051^{***}
	(0.007)	(0.008)
Controlfunction Shuttle Time	0.063^{***}	0.058^{***}
	(0.0003)	(0.0002)
Controlfunction Cab Time	0.037^{***}	0.034^{***}
	(0.001)	(0.001)
Adopter.s	1.343^{***}	1.123^{***}
	(0.004)	(0.004)
Adopter.c	-1.171^{***}	-1.452^{***}
	(0.005)	(0.004)
Recent Week Rides.s	0.792^{***}	0.774^{***}
	(0.002)	(0.002)
Recent Week Rides.c	0.641^{***}	0.634^{***}
	(0.004)	(0.004)
Market Controls	Yes	Yes
Observations	693,455	609,958
R^2	0.693	0.721

Table 9 Parameter estimates from alternative specification with adoption groups..s and .c are shuttle- and cab-specific coefficients. 1 and 2 are coefficients for the two customer adoption groups (early and late adopters) (*,,*** indicates statistical significance at 10%,5%,1% level)**

	(Morning)	(Evening)
Shuttle Intercept	−11.131*** (0.154)	−14.798*** (0.163)
Cab Intercept	−16.895*** (0.173)	−15.124*** (0.194)
$Price_1$	−0.0174*** (0.0002)	−0.0132*** (0.0002)
$Price_2$	−0.0136*** (0.0002)	−0.0102*** (0.0002)
$Price_3$	−0.0105*** (0.0001)	−0.0085*** (0.0001)
$Price_4$	−0.0077*** (0.0001)	−0.0064*** (0.0001)
$Wait_1$	−0.165*** (0.001)	−0.153*** (0.001)
$Wait_2$	−0.145*** (0.001)	−0.133*** (0.001)
$Wait_3$	−0.121*** (0.001)	−0.107*** (0.001)
$Wait_4$	−0.097*** (0.001)	−0.086*** (0.001)
Frequency	0.094*** (0.0009)	0.087*** (0.0007)
Time	−0.010*** (0.0001)	−0.010*** (0.0001)
Commute	−1.014*** (0.009)	−0.974*** (0.010)
Distance	−0.226*** (0.006)	−0.141*** (0.005)
Control function Shuttle Price	−0.027*** (0.0002)	−0.031*** (0.0002
Control function Cab Price	0.005*** (0.0002)	0.006*** (0.0002)
Control function Cab Wait	0.075*** (0.006)	0.084*** (0.007)
Control function Shuttle Time	0.012*** (0.0002)	0.013*** (0.0002)
Control function Cab Time	0.035*** (0.001)	0.041*** (0.001)
Recent Week Rides.s	0.817*** (0.002)	0.849*** (0.002)
Recent Week Rides.c	0.432*** (0.006)	0.457*** (0.009)
Market Controls	Yes	Yes
Observations	693,455	609,958
R^2	0.557	0.612

Table 10 Parameter estimates from alternative definition with distance-dependent sensitivities.s and .c are shuttle- and cab-specific coefficients.(*,,*** indicates statistical significance at 10%,5%,1% level)**

C.3.5. Alternate Definition of market sizes To test the robustness of our results to market size definitions, (a) We calculate the size of the outside option for each market separately for the morning and evening periods–i.e., we make the definition of the market size time dependent. (b) To account for residential clusters, we include population density as a metric in computing the size of the outside option. We note that Google Place clusters do not contain explicit information on residential clusters. A place with many Google places like convenience stores and salons will likely have a higher residential population. However, for a cleaner construction of the market size, we use population density to compute market size. (c) We assign weights to different Google clusters while deciding the proportionality factor.

To calculate the weights for different Google clusters, we run the following regressions (separately for the morning and evening hours) to determine which Google clusters predict higher cab usage across different markets. That is, we use different Google categories to explain the cab ridership on a route jk.

$$log(\#cabrides)_{jk} = a_1.\#category^1_k + a_2.\#category^2_k + \ldots + a_{11}population + epsilon_{jk} \tag{10}$$

where a_i are the coefficients for different Google categories and populations.

We then use these weights to allocate originating traffic from a location j to different k's, based on the distribution of Google place categories at k. Weights for each category i are defined as $w_i = \frac{e^{a_i}}{e^{a_1}+\ldots+e^{a_{11}}}$. Thus, weights differ for different Google place categories, residential clusters, and, more importantly, across the morning and evening hours. We estimate the model using market sizes that use this allocation of Google Place clusters. Table 13 provides the results using this weighting scheme. We find that our results are largely robust to this specification of market size.

C.4. Testing Instrument Strength and Validity

Instrument Strength We test the strength of instruments following the general rule of thumb as per Staiger and Stock (1997) and Stock and Yogo (2005). Specifically, we include F-statistic values from the reduced form first stage regressions in the paper. We also reproduce the results here, in Table 14. All our F-stat values are more than 10, indicating that our instruments are strong.

	Latent Class Analysis
Shuttle Intercept	-17.211^{***}
	(0.053)
Cab Intercept	-13.121^{***}
	(0.069)
Price Paid.1	-0.0132^{***}
	(0.0002)
Price Paid.2	-0.0091^{***}
	(0.0003)
Wait.1	-0.153^{***}
	(0.003)
Wait.2	-0.108^{***}
	(0.002)
Time.1	-0.010^{***}
	(0.0001)
Time.2	-0.011^{***}
	(0.0002)
Commute.1	-1.053^{***}
	(0.006)
Commute.2	-1.032^{***}
	(0.003)
Distance	-0.124^{***}
	(0.002)
Frequency.1	0.079^{***}
	(0.0003)
Frequency.2	0.082^{***}
	(0.0001)
Controlfunction Shuttle Price	-0.026^{***}
	(0.0001)
Controlfunction Cab Price	0.004^{***}
	(0.0001)
Controlfunction Cab Wait	0.070^{***}
	(0.003)
Controlfunction Shuttle Time	0.012^{***}
	(0.0002)
Controlfunction Cab Time	0.033^{***}
	(0.001)
Weight Param	-0.0124***
	(0.0002)
Observations	1,323,413
R^2	0.635

Table 11 Estimates from the latent class model. .1 and .2 refer to. two latent classes

Discussion: We also note that we have selected our instruments following (Belloni et al. 2012, 2011). The procedure aims at selecting a stronger set of instrumental variables from a larger set using machine learning methods. In this regard, we are working with a strong set of instruments that strengthen the first stage of the estimation and are not surprised that our instruments pass the formal tests for identifying weak instruments.

Instrument Exogeneity

To test for the exogeneity of instruments, we follow Guevara (2018) and perform the Amemiya-Lee-Newey (ALN) test, which is a state-of-the-art method for testing the exogeneity of instruments. Specifically, we have the following two-stage control function model (simplified here for exposition with price as the endogenous variable):

$$U_{ijka} = \beta_a + \beta_p p_{jka} + \Theta' X_{jk} + \varepsilon_{ijka} \tag{11}$$

where, customer i chooses alternate a in market jk and the utility she obtains is a function of prices p_{ijka} and an exogenous market level variables contained in the vector X_{jk}. The prices are modeled as a function of the instruments and the exogenous variables in stage one of the estimation. Specifically,

$$p_{jka} = \alpha + \alpha_1 z_{1jka} + \alpha_2 z_{2jka} + \cdots + \alpha_{m+n} z_{(m+n)jka} + \Theta' X_{jk} + \xi_{jka} \tag{12}$$

Explanatory Variable	*Morning*	*Evening*
Shuttle intercept	-10.437^{***}	-14.824^{***}
	(0.143)	(0.151)
Cab intercept	-17.424^{***}	-15.257^{***}
	(0.166)	(0.181)
Price Paid	-0.018^{***}	-0.012^{***}
	(0.0004)	(0.0004)
Wait	-0.145^{***}	-0.134^{***}
	(0.002)	(0.002)
Frequency	0.403^{***}	0.363^{***}
	(0.010)	(0.012)
Time	-0.010^{***}	-0.010^{***}
	(0.0002)	(0.0002)
Commute	-1.119^{***}	-0.943^{***}
	(0.013)	(0.012)
Distance	-0.241^{***}	-0.113^{***}
	(0.006)	(0.005)
Controlfunction Shuttle Price	-0.024^{***}	-0.029^{***}
	(0.0002)	(0.0004)
Controlfunction Cab Price	0.006^{***}	0.006^{***}
	(0.0003)	(0.0003)
Controlfunction Cab Wait	0.075^{***}	0.090^{***}
	(0.008)	(0.006)
Controlfunction Frequency	0.069^{***}	0.055^{***}
	(0.004)	(0.005)
Controlfunction Shuttle Time	0.014^{***}	0.012^{***}
	(0.0002)	(0.0002)
Control function Cab Time	0.036^{***}	0.034^{***}
	(0.001)	(0.002)
Recentweekrides.s	0.817^{***}	0.840^{***}
	(0.002)	(0.002)
Recentweekrides.c	0.647^{***}	0.678^{***}
	(0.009)	(0.007)
Market Controls	Yes	Yes
Observations	625,811	567,919
R^2	0.663	0.687

Table 12 Estimates from the choice model with distances greater than 2 km. .s and .c are shuttle- and cab-specific coefficients. (*,,*** indicates statistical significance at 10%,5%,1% level)**

where we have $n+m$ instruments for prices, n for shuttle price and m for cab price. Substituting (2) in (1), we get,

$$U_{ijka} = \underbrace{\beta_a + \beta_p\alpha}_{\pi_0} + \underbrace{\beta_p\alpha_1 z_{1jka}}_{\pi_1} + \underbrace{\beta_p\alpha_2 z_{2jka}}_{\pi_2} + \cdots + \underbrace{\beta_p z_{(m+n)jka}}_{\pi_{m+n}} + \underbrace{\Theta' X_{jk} + +\beta_p\Theta' X_{jk}}_{\pi_{m+n+1}} + \underbrace{\varepsilon_{ijka} + \beta_p\xi_{jka}}_{\varepsilon^*_{ijka}} \quad (13)$$

We estimate the reduced form model (3) by logit and get $\hat{\pi_0}, \hat{\pi_1}, \hat{\pi_2}, \cdots \pi_{n+\hat{m}+1}$ directly. Lee (1982) and Ruud (1983) show that logit estimation of the model produces consistent estimators. The same is noted by Guevara-Cue (2010). Note that $\hat{\pi_i}\ \forall\ i \in \{1,..n+m\}$ estimated above produce a set of $n+m$ identifying conditions for β_p. Specifically,

$\hat{\pi}_1 = \beta_p\hat{\alpha}_1$

$\vdots$

$\hat{\pi}_{n+m} = \beta_p\hat{\alpha}_{n+m}$

The above system of equations can be thought of as observations from $\hat{\pi} = \beta_p\hat{\alpha} + w$, where w is the Gaussian error term. This is because the equations can't be satisfied exactly for any value of β_p. We construct the minimum chi-square estimator as in Guevara (2018) : $\min_{\beta_p} (\hat{\pi} - \beta_p\hat{\alpha})' \hat{W}^{-1} (\hat{\pi} - \beta_p\hat{\alpha})$, where $\hat{W}$ is constructed using the (i) variance-covariance matrices of the instruments in the first stage regressions and in the model estimated in (3), and (ii) the OLS estimator $\hat{\beta_p}$: $\hat{\pi} = \beta_p\hat{\alpha} + w$.

In our paper, we have a total of 18 instruments for price. Hence, for price, W is an 18×18 matrix, and $\hat{\pi} - \beta_p\hat{\alpha}$ is an 18×1 column vector. $G_{ALN} = \frac{1}{18}\left(\hat{\pi} - \hat{\beta}_p\hat{\alpha}\right)' \hat{W}^{-1}\left(\hat{\pi} - \hat{\beta}_p\hat{\alpha}\right) \sim \chi^2_{df}$, where the degrees of freedom $= n+m-1$.

Explanatory Variable	*Morning*	*Evening*
Shuttle intercept	-8.459^{***}	-12.189^{***}
	(0.149)	(0.143)
Cab intercept	-15.319^{***}	-14.824^{***}
	(0.155)	(0.163)
Price Paid	-0.016^{***}	-0.011^{***}
	(0.0005)	(0.0004)
Wait	-0.136^{***}	-0.124^{***}
	(0.001)	(0.001)
Frequency	0.403^{***}	0.372^{***}
	(0.010)	(0.013)
Time	-0.011^{***}	-0.010^{***}
	(0.0001)	(0.0002)
Commute	-1.118^{***}	-0.943^{***}
	(0.013)	(0.012)
Distance	-0.229^{***}	-0.108^{***}
	(0.007)	(0.006)
Controlfunction Shuttle Price	-0.024^{***}	-0.029^{***}
	(0.0002)	(0.0003)
Controlfunction Cab Price	0.005^{***}	0.005^{***}
	(0.0003)	(0.0003)
Controlfunction Cab Wait	0.081^{***}	0.094^{***}
	(0.008)	(0.006)
Controlfunction Frequency	0.071^{***}	0.056^{***}
	(0.004)	(0.005)
Controlfunction Shuttle Time	0.017^{***}	0.014^{***}
	(0.0002)	(0.0002)
Control function Cab Time	0.037^{***}	0.036^{***}
	(0.001)	(0.001)
Recentweekrides.s	0.842^{***}	0.863^{***}
	(0.002)	(0.001)
Recentweekrides.c	0.668^{***}	0.697^{***}
	(0.008)	(0.009)
Market Controls	Yes	Yes
Observations	693,455	609,958
R^2	0.668	0.695

Table 13 Estimates from the choice model using different proportionality weights for google place clusters .s and .c are shuttle- and cab-specific coefficients. (*,,*** indicates statistical significance at 10%,5%,1% level)**

	Shuttle Price	Cab Price	Shuttle Time	Cab Time	Cab wait	Shuttle Frequency
F-Statistic (SS)	50.91	194.32	84.99	125.90	32.57	90.44
Critical value	10	10	10	10	10	10
Reject H_0	Reject	Reject	Reject	Reject	Reject	Reject

Table 14 Tests of Weak instruments

Similarly, W has dimension 10×10 for time and 3×3 for cab wait. Table 15 reports the χ^2 statistic computed for all the endogenous regressors, along with the p-value and the critical χ^2 value at p=0.01.

	Price	Travel Time	Cab Wait	Shuttle Frequency
Statistic	22.583	7.2315	3.1223	5.6321
Df	17	9	2	3
p-value	0.1633	0.6130	0.2098	0.1309
Critical Value (p=0.01)	33.4	21.7	9.21	11.22

Table 15 ALN test for endogenous regressors.

We see from Table 15 that the p-values from the ALN tests for all the variables are greater than 0.10. Hence, the null hypotheses of valid instruments are not rejected for any of the endogenous variables.

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