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DOES UBER BENEFIT TRAVELERS BY PRICE DISCRIMINATION?

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Abstract

We use Uber fare data for passenger trips from Los Angeles (LAX), New York (JFK), and San Francisco (SFO) airports to hotels in those metropolitan areas to test whether Uber engages in third-degree price discrimination by charging higher fares to travelers who originate from the same airports as other travelers but who stay at more expensive hotels. We find that fares are positively and statistically significantly related to the price of hotel rooms. Importantly, we also find that allowing ridesharing companies to price discriminate improves travelers' welfare, on average, by increasing their travel options.

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1. Introduction

Price discrimination by firms—the practice of charging consumers based on what they are willing to pay—is common and generally legal. Economists study the practice because its welfare effects on consumers may be ambiguous (Schmalensee (1981), Varian (1985), Holmes (1989), Corts (1998), Aguirre, Cowan, and Vickers (2010), and Cowan (2016)); it attracts the attention of antitrust authorities if it harms competition (Carlton and Heyer (2008), Carlton and Waldman (2014)); and it requires careful empirical work to confirm its existence (Shepard (1991), Borenstein and Rose (1994), Morrison and Winston (1995), Gerardi and Shapiro (2009), and Luttman (2019)).

Because ridesharing companies can segment market demand and because their fares, unlike taxi fares, are not regulated, they have been criticized for practicing a form of price discrimination—characterized as surge pricing—during periods of excess demand. However, ridesharing companies have received little attention for whether they price discriminate as a matter of policy and, if so, how travelers' welfare is affected. Uber, the largest ridesharing company in the world, used to set its fares solely in accordance with the distance and duration of a trip and the level of demand at the origin.[1] But since at least 2017, UberX, the most heavily used of Uber's services (Cohen et al. (2016)), has charged different prices based on travelers' destinations, which we argue is a form of third-degree price discrimination.[2] Anecdotal evidence presented in Exhibit

[1] Hwang, Winston, and Yan (2021) find that Uber provides large annual benefits to urban travelers.

[2] Biz Carson, "Uber May Charge You More Based on Where You Are Going," Business Insider, May 20, 2017 reports that UberX fares may vary according to a traveler's destination. This pricing system is hidden from drivers and riders and uses a machine-learning algorithm to predict travelers' willingness to pay for its ride service and to differentiate fares across routes. As noted, Uber also applies a dynamic pricing algorithm, surge pricing, to adjust short-term rider-to-driver fluctuations. Besides UberX, Uber's other services include UberXL and UberBlack, featuring SUVs or luxury vehicles, and UberPool, a carpooling service. UberX fares are lower than the fares charged by UberXL and UberBlack, but higher than the fares charged by UberPool.

1 suggests that Uber also charges different prices to the same destination from similar origins with a higher rate if the origin is a hotel.

The purpose of this paper is to investigate whether Uber price discriminates by using the extensive fare data generated by UberX for trips originating from the major airports in Los Angeles (LAX), San Francisco (SFO), and New York (JFK) to hotels in those metropolitan areas.[3] UberX fare data are attractive to use for this purpose because the origin of a trip is clearly indicated, thereby enabling us to control for the heterogeneity of demand, and because Uber can identify and segment distinct travel markets at the destination that vary by a hotel's average room rate. We hypothesize that travelers staying at hotels with higher average room rates will be charged higher UberX fares because they have signaled that they are likely to have higher reservation prices for their local transportation than travelers who stay at hotels with lower average room rates; we hypothesize that those travelers will be charged lower UberX fares because they have signaled that they are likely to have lower reservation prices for their local transportation.

In order to test the hypothesis, we randomly selected 700 routes that originated at Los Angeles International Airport (LAX), John F. Kennedy International Airport (JFK), and San Francisco International Airport (SFO) and terminated at hotels located within a 20-mile radius of each airport. We group the hotels into zones with a 0.1-mile radius. We collected high-frequency data (every 20 minutes) for UberX trips, including fares, estimated travel time of the trip (duration), and trip distance, on those routes from September 1, 2018 to November 30, 2018. Data collection is accomplished by an automated process that uses Uber's open API (application programming interface) service from multiple computers registered with homogeneous travelers' characteristics. Although the data are not generated by actual trips, the values of the variables should be the same

[3] In 2015, Los Angeles, New York, and San Francisco were Uber's largest markets in the United States (Cohen et al. (2016)).

as those generated by travelers who took those trips.[4] Our final sample consists of a balanced panel of travelers that allows us to exploit the variation in fares across trips with the same origin, the same destination zone, and the same requested pickup time.

We find that Uber does price discriminate because fares increase by \$0.10 to \$0.54 per ride for each \$100 increase in the hotel room rate, after controlling for traffic conditions affecting the fare.[5] One might criticize Uber's pricing policy on the grounds that it is intended primarily to increase its profits by targeting more affluent passengers, who are traveling to more expensive metropolitan area destinations. However, price discrimination also may have positive welfare effects, such as reducing prices to attract travelers who might otherwise not consider the service and rewarding travelers for purchasing service in less popular markets. Thus, we explore empirically the welfare implications of ridesharing's third-degree discriminatory fare structure in the transportation market comprised of New York JFK airport to metropolitan-area hotels by comparing its economic effects with those of a uniform fare, which could be mandated by a regulation that prohibits ridesharing companies from setting discriminatory fares. We find that Uber's pricing scheme raises travelers' welfare for most trips, in all likelihood by expanding their travel options.

[4] Our pricing models are appropriately interpreted as offer functions (Rosen (1974)) because a traveler could reject the offer of an Uber trip based on the fare or other variables related to the trip.

[5] The fare increases correspond to a 0.25% to 1.7% increase per ride for each \$100 increase in the hotel room rate. Given that we calculate the percentage changes as:
(dollar amount/sample mean of the ride fare)*100, where the sample means are \$31.61, \$64.56, and \$31.46 for Los Angeles, New York, and San Francisco, respectively, the percentage changes are larger for shorter distance trips.

2. Theoretical Perspectives on Route-Based Price Discrimination

We use a theoretical framework developed by Cowan (2016) and Varian (1985) to indicate conditions under which Uber's route-based pricing policy can be interpreted as third-degree price discrimination that could raise social welfare.[6] Assume passengers at a given origin consider taking Uber to travel on routes *A* and *B*, which use the same roadway to get to different destinations. Because travelers who journey to those destinations are different, the markets are segmented by different distributions of their reservation prices. Let θ denote travelers' average reservation price for an Uber trip in a market and assume that the average reservation price of a trip in market *A* is greater than the average reservation price of a trip in market B, $\theta_A > \theta_B$. Further assume that a passenger's utility from an Uber trip in market *i* is given by a quasi-linear and strictly concave utility function, $U(q_i)$, where $i = A, B$ and q_i is the quantity of trips per traveler. The total quantity of trips in a market, $Q_i(p_i) = n_i q_i(p_i)$, is determined by the number of travelers, $n_i > 0$, and the quantity of trips per traveler as a function of the (discriminatory) price, p_i, in market *i*. We denote a uniform price that does not vary by market by $\bar{p}$.

Finally, we assume a constant marginal cost per Uber trip, c_{UB}, that includes the Uber driver's profit (or wage), π_d and the marginal production cost per trip (including gas expenditure and vehicle depreciation), c_d; thus, $c_{UB} = \pi_d + c_d \geq 0$. We do not have data on Uber's costs, but we are not aware of institutional or empirical evidence suggesting that Uber's costs are subject to increasing or decreasing returns.

If a traveler chooses a route for a trip in Uber's app, then Uber offers the traveler a fare for that trip, and if the traveler's reservation price is lower than the offered fare, she would reject the offer. Conversely, if her reservation price is higher than or equal to the offered fare, she would accept the offer. Given the information generated by repeated interactions between Uber and

[6] Tirole (1988) provides a general treatment of third-degree price discrimination.

travelers in market *i*, we assume that Uber knows the distribution of travelers' reservation prices for routes *A* and *B*.

To further the analysis, we follow Cowan (2016) and assume that the distribution of reservation prices is derived from a logistic function with different means, $\theta_A > \theta_B$, but a common standard deviation, σ. The results of the analysis are not sensitive to the assumed logistic distribution of reservation prices because Cowen (2016) shows that the conclusions drawn from a logistic distribution also can be drawn from alternative distributions, such as Pareto and exponential. Nevo and Wolfram (2002) derive general conditions for profit-maximizing third-degree price discrimination behavior in the context of couponing.

The reservation price distributions can then be transformed into logistic demand functions where the corresponding inverse demand function for market *i* is given by: $p_i(Q_i) = \theta_i - \sigma \ln\big((Q_i/n_i)/(1 - Q_i/n_i)\big)$. This leads to a proposition that third-degree price discrimination is the result of profit maximization by firms that know the distribution of consumers' reservation prices.[7]

Proposition 1. *If a firm maximizes profit from the segmented markets characterized by consumers' inverse demand functions derived from a logistic distribution of reservation prices, then there exist profit-maximizing discriminatory prices, p_A^* and p_B^*, such that the uniform price, $\bar{p}^*$, which maximizes the firm's profit lies between the discriminatory prices, p_A^* and p_B^*, ($\bar{p}^* \in [p_A^*, p_B^*]$).)*

Proof. Proposition 1 is true if it satisfies Theorem 1 in Nahata, Ostaszewski, and Sahoo (1990), which states that the profit function in each market is a continuous function with a global

[7] In a dynamic setting, the difference in prices across markets may change over time to reflect the change in the distribution of consumers' reservation prices. In our empirical analysis, we test for this possibility by exploring whether our findings are sensitive to the temporal distribution of Uber trips.

maximum in the price. Because the demand function in our case is twice-continuously differentiable and because marginal revenue is strictly decreasing in quantity, then under monopoly pricing, there is a unique interior solution, Q_i^*, which maximizes profit from markets *A* and *B*. Cowan (2016) argues that only one profit-maximizing price exists because of the unique interior solution, Q_i^*, and because demand is downward sloping, which implies that the condition in Theorem 1 of Nahata, Ostaszewski, and Sahoo holds.

Turning to the welfare implications of third-degree price discrimination, the upper and lower bounds on the welfare change from discriminatory pricing derived by Varian (1985) imply that a necessary condition for welfare to increase is that a change from uniform pricing to price discrimination causes an increase in quantity. Cowan (2016) proves that the necessary condition holds for the (inverse) demand function used here; thus, the following proposition states the sufficient condition for a welfare improvement.

Proposition 2. *Given the logistic demand functions, social welfare under route-based price discrimination is higher than under uniform pricing.*

Proof. Social welfare, *W*, is the sum of consumer surplus and the profits of Uber and Uber drivers. Varian's (1985) welfare bounds identify the change in social welfare from the change from uniform pricing to third-degree price discrimination:

$$(\bar{p} - c_d)\sum_i \Delta Q_i > \Delta W \ > \ \sum_i (p_i - c_d)\Delta Q_i. \qquad (1)$$

We need to prove that the right-hand side of the second inequality is greater than zero, $(\sum_{\mathrm{i}}(\mathrm{p_i} - \mathrm{c_d})\Delta \mathrm{Q_i} > 0$. Given the production marginal cost $\mathrm{c_d} = \mathrm{c_{UB}} - \pi_{\mathrm{d}} \le \mathrm{c_{UB}}$ where $\pi_{\mathrm{d}} \ge 0$, then $\sum_{\mathrm{i}}(\mathrm{p_i} - \mathrm{c_d})\Delta \mathrm{Q_i} \ge \sum_{\mathrm{i}}(\mathrm{p_i} - \mathrm{c_{UB}})\Delta \mathrm{Q_i}$. Thus, it is sufficient to show that $\sum_{\mathrm{i}}(\mathrm{p_i} - \mathrm{c_{UB}})\Delta \mathrm{Q_i} > 0$.

Cowan (2016) proved that the following equality holds: $(p_i - c_{UB})\Delta Q_i + \sigma n_i \pi_i'(\bar{p}) = (1 - \bar{q_i}) n_i \big(\pi_i(p_i) - \pi_i(\bar{p})\big)$, where $\bar{q_i} = q_i(\bar{p})$ and $\pi_i(p)$ is the profit obtained from market *i* given price p. Thus, the term of interest, $\sum_i (p_i - c_{UB})\Delta Q_i$, satisfies the following equality:

$$\sum_i (p_i - c_{UB})\Delta Q_i = \sum_i n_i\big[(1-\bar{q_i})\big(\pi_i(p_i) - \pi_i(\bar{p})\big) - \sigma\pi_i'(\bar{p})\big]$$
$$= \sum_i (1-\bar{q_i})n_i\big(\pi_i(p_i) - \pi_i(\bar{p})\big) \qquad (2)$$

because $\sum_i n_i\pi_i'(\bar{p}) = 0$, which is the first-order condition for profit maximization under uniform pricing. Given $1-\bar{q_i} > 0$, $n_i > 0$, and $\big(\pi_i(p_i) - \pi_i(\bar{p})\big) \geq 0$ by Theorem 1 of Nahata, Ostaszewski, and Sahoo (1990), then $\sum_i (1-\bar{q_i})n_i\big(\pi_i(p_i) - \pi_i(\bar{p})\big) > 0$, which satisfies the sufficient conditions for a positive welfare effect given by the Varian (1985) welfare bounds.[8]

As noted, we assume different means and a common standard deviation for the distribution of reservation prices for markets *A* and *B*. However, the magnitude of the standard deviation can affect the difference in welfare between uniform and discriminatory pricing because an increase in the standard deviation of reservation prices can cause the distribution of the reservation prices of the two pricing regimes to overlap more extensively, thereby decreasing the gains from discriminatory pricing. Accordingly, the standard deviation of the price distributions must be sufficiently small for discriminatory pricing to generate significant welfare improvements.[9]

In sum, if the distribution of travelers' reservation prices is derived from a logistic function with different means and the same standard deviation, and if the firm is well-informed about the distribution, then third-degree discriminatory pricing is profit maximizing. As noted, this conclusion can be obtained if we assume alternative distributions of travelers' reservation prices. The discriminatory pricing regime also increases social welfare if the standard deviation of

[8] Cowan (2016) proves that Varian's necessary condition, which is the left-hand side inequality in equation (1), holds.

[9] It is possible that some travelers could respond to price discrimination by shifting their travel to the route with the lower fare, but this response is unlikely unless travelers also are willing to change their activity by going to a new destination that provides utility that is comparable to the utility provided by the original destination. Travelers also have less incentive to shift routes as the standard deviation of reservation prices increases because the discriminatory prices converge to the uniform price.

reservation prices is sufficiently small. We now explore the influences on Uber's fares in actual markets to see if we can draw any conclusions from the data about Uber's price discrimination behavior and the welfare implications.

3. Research Design

The preceding theory guides an empirical test of price discrimination behavior by Uber if we define distinct markets where travelers are likely to have different reservation prices and Uber has the information to infer them, and if we can control for other important influences on fares that do not reflect price discrimination. We briefly describe a travel setting that is conducive to such an empirical test and then summarize our data and identification strategies.

Transportation markets that consist of an airport at the origin and a hotel at the destination are attractive for our empirical test because hotel room rates are likely to reflect travelers' reservation prices, whereby travelers who stay at hotels with higher room rates are more likely than travelers who stay at hotels with lower room rates to have higher reservation prices for their local transportation and to be offered higher fares for trips on Uber X. Uber is likely to know the distribution of travelers' reservation prices based on the information generated by repeated interactions between Uber and travelers in transportation markets defined by an airport and hotels with different room rates. Thus, the key empirical relationship in our test of Uber's price discrimination behavior is the effect of hotels' average room rates on Uber X fares.

We obtain a consistent estimate of this relationship by controlling for other important influences on Uber X fares in those markets. Because the routes to different hotels originate from the same airport, we use time fixed-effects to control for the influence of local demand and possible shocks to the supply of drivers at the airport on fares. We control for important unobserved characteristics at the destination by using geographic "matching" to group destination hotels within a 0.1-mile radius. We also control for the primary trip characteristics, route distance and duration, which are likely to affect Uber X's fare. Finally, we make the plausible assumption that travelers who originate from the same airport and stay at the same hotel have homogeneous reservation prices for local transportation. Given this assumption and the preceding controls, we infer that the remaining fare difference between the two routes that are segmented by hotel room rates is caused by Uber's price discrimination behavior. As noted, Uber perceives that the markets in our analysis are segmented, as assumed under third-degree price discrimination, because it has been using "route-based pricing" since at least 2017.[10]

Data

We compile an extensive data set using Uber's API that contains the fare, distance, duration, and wait time for the arrival of Uber X for millions of trips, which, as noted, Uber would have provided with little change to the values of the variables if the trips were confirmed by travelers. The sample was collected every twenty minutes from September 1, 2018 to November 30, 2018 for roughly 700 routes that originated at Los Angeles International Airport (LAX), John F. Kennedy International Airport (JFK), and San Francisco International Airport (SFO) and that terminated at hotels located within a 20-mile radius of each airport. It is possible that Uber could identify the exact location of travelers using GPS software to set fares that discriminate based on different origins at the airport, such as domestic and international terminals; however, we are not aware of any evidence that Uber sets fares in that fashion. In addition, we collected data by requesting Uber services from multiple servers, which could use only the airport as the origin.

[10] It is possible that travelers could avoid the cost of a higher discriminatory fare by programming Uber to take them to a cheaper hotel and then walking with their luggage to their preferred more expensive hotel. We assume that such behavior is unlikely to occur sufficiently often to affect our findings.

We obtained the locations, room rates, and ratings of the hotels from the American Automobile Association (AAA). The AAA Diamond Ratings range from one to five diamonds and reflect a combination of the overall quality, range of facilities, and level of services offered by the property. We used the AAA ratings information to confirm the relationship between hotel room rates and hotel quality; that is, travelers pay higher room rates to stay at higher quality hotels. Figure 1 identifies the location of each airport and the hotels located within twenty miles of it that are included in the sample. Most of the hotels in New York are in Manhattan; thus, the Uber X trips in New York take longer and travel farther than the Uber X trips in San Francisco and Los Angeles do because most of the hotels in those California markets are closer to the airport.

Table 1 presents summary statistics for the fares, trip characteristics, and hotel room rates for each airport in the sample. Consistent with figure 1, the longest, most time-consuming, and therefore most expensive Uber X trips are taken in New York. Trips in Los Angeles and San Francisco have similar fares even though trips in Los Angeles take longer and travel a greater distance. We speculate that this may reflect the fact that public transit is a more competitive travel option for travelers in airport-hotel transportation markets in San Francisco than it is for those markets in Los Angeles. For example, the Bay Area Rapid Transit System has a station at the San Francisco Airport where travelers can take trains to downtown San Francisco and other Bay Area destinations, but the Los Angeles Metro Rail System does not directly serve Los Angeles Airport. The duration of trips per mile suggest that passengers in Los Angeles and New York spend more time stuck in traffic than passengers in San Francisco do. It also takes longer for Uber X to pick up a passenger in those cities, in all likelihood because roads to the airport are more congested and because of differences in the demand for Uber X trips and the supply of drivers.

Given how we compiled our sample, the hotels were chosen randomly. The hotel room rates apply to the same season, September to November, so we collected them for the first week of the sample period, and we used the average room rate for each hotel in the empirical analysis.[11] New York and San Francisco have the highest hotel room rates.

Preliminary Evidence of Hotel-Based Price Discrimination

We first use the data to explore the variation in UberX fares between "homogeneous" markets by constructing pairs of routes where destination hotels are less than 0.1 mile apart from each other. We compute the average fare-difference between a matched pair over the sample period and plot the distribution of the pair-wise fare-differences across pairs in Figure 2. The graphs suggest that Uber uses hotel characteristics as inputs to design a route-based pricing algorithm because the distributions of the pair-wise fare differences are broad, and they include a notable share of large fare differences. We confirm the effect of hotel prices on fares econometrically by holding other possible influences on fares constant.

Identification Strategies

We estimate a hedonic pricing model with time fixed-effects to control for unobserved temporal influences given by:

$$P_{jt} = \beta \, HP_{jt} + \gamma_0 + \gamma_1 Distance_{jt} + \gamma_2 Duration_{jt} + \sum_{t=1}^{T} \psi_t Time_t + \epsilon_{jt}, \qquad (3)$$

where P_{jt} is the UberX fare for route j at time *t*; HP_{jt} is the average room rate of the hotel at the endpoint of route j; $Distance_{jt}$ and $Duration_{jt}$ are trip distance and duration per mile, respectively, $Time_t$ is time fixed-effects that are specified as a set of dummy variables, including hour of the day and day of the week, ψ represents the fixed effects parameters, and ε is an error term. The duration of an Uber trip captures congestion on the road and congestion at the destination, which could vary according to the size of the hotel. Thus, it captures the effect of hotel size on Uber fares. The time fixed-effects capture variations in demand at the airport origin on the

[11] We found no evidence that the hotel room rate was correlated with either the distance of the hotel from the airport (trip origin) or with the duration of the trip from the airport.

Uber X fare that are caused by the distribution of hourly and daily flights that arrive at the airport. Finally, we specify duration per mile instead of duration to avoid collinearity with distance.

We specified a linear functional form for the hedonic pricing model. For sensitivity purposes, we also estimated hedonic pricing models that specified the natural log of Uber X fares and the natural log of hotel prices and we obtained very similar results to those based on the linear model in equation (3).

Our estimates could be affected by unobserved factors that vary with hotels that are located far from each other. To address this possibility, we estimate a geographic "matching" regression model to control for travel conditions along the route and for unobserved destination characteristics more directly, which assumes that hotels within a 0.1 mile radius of each other experience identical travel conditions along the route and do not differ in important unobserved characteristics associated with the destination. This model enables us to test for the presence of price discrimination even when Uber X trips are made over virtually the same stretch of road.

The effect of the matching assumption, as shown in figure 3, is to compress the destinations in Los Angeles, New York, and San Francisco and to make them less separated than the destinations that we showed in figure 1. The assumption also reduces the number of distinct routes and the sample sizes because some hotels do not have "neighbors" that are within a 0.1-mile radius.

We specify the geographic matching regression model as:

$$P_{jt} = \beta_0\, LocHP_{jt} + \beta_1\, DLocHP_{jt} + \gamma_0 + \gamma_1 Distance_{jt} + \gamma_2 Duration_{jt} + \sum_{t=1}^{T} \psi_t Time_t + \epsilon_{jt}, \tag{4}$$

where $LocHP_{jt}$ is the *mean* of the average room rates of the hotels within a 0.1 mile radius of the hotel on route j at time t, and $DLocHP_{jt}$ is the *difference* between the average room rate of the hotels within a 0.1 mile radius of the hotel on route j at time t and the average room rate of the hotel on route *j* at time *t*, namely HP_{jt}. $LocHP_{jt}$ measures the average price of neighboring hotels so that a positive β_0 suggests that higher average room rates of nearby hotels are associated with higher passenger fares, while the coefficient for $LocHP_{jt}$, β_1, indicates how fares vary with the difference between the room rate of a hotel on route *j* and the average room rate of neighboring hotels. Both variables help test for the presence of price discrimination within a small area, controlling for the heterogeneity in travel conditions as well as for other possible unobserved influences on the Uber X fare associated with the area where a hotel is located.

As shown in table 2, the average number of hotels that we can match for each group of hotels is 2.36, 4.04, and 3.84 in Los Angeles, New York, and San Francisco, respectively. The average for Los Angeles is lower than the average for New York and San Francisco because the density of hotels in Los Angeles is lower than the density of hotels in those other cities. The average room rates of the grouped hotels are not notably different from the average room rates of the individual hotels (see table 1). But grouping does reduce the number of distinct hotels in the sample and the sample size because hotels without close neighbors are no longer included. Finally, the table also shows that, on average, the difference between the average room rate of a hotel on a route in the matched sample and the average price of its neighboring hotels is generally small and not statistically significantly different from zero in all of the cities. As expected, a small geographical area is likely to encompass hotels with similar room rates.

4. Estimation Results

We report ordinary least squares (OLS) parameter estimates of the base case hedonic pricing model given in equation (3) in table 3 using all the trips from a given airport to a hotel. We report separate estimation results for each city, and we specify the average room rate for a hotel on a given route in two alternative ways: a dummy variable indicating whether a hotel's average room rate exceeds the median hotel room rate of all the hotels at the destinations, $HighHP$, and, as discussed previously, a hotel's average room rate, HP.

We find that the estimated coefficients for both specifications provide evidence of price discrimination by Uber X because they are positive and statistically significant for all the airports. The estimates in columns (1), (3), and (5) indicate that a passenger taking an Uber X trip to a hotel that has a room rate that exceeds the median room rate would pay, on average, $1.03, $0.85, and $0.63 more for their trip in Los Angeles, New York, and San Francisco, respectively. The estimates in columns (2), (4), and (6) indicate that a passenger would pay $0.54, $0.16, and $0.10 more for their trip in Los Angeles, New York, and San Francisco, respectively, for each $100 increase in a hotel's average room rate.[12] Finally, as expected, trip distance and duration have a positive effect on fares and the coefficients are statistically significant. The effect of trip duration on fares varies considerably by region—the effect of distance varies much less—which may be due to differences in the fare structures or travel conditions.

The parameter estimates presented in table 4 of the matching model given in equation (4) also provide evidence that Uber engages in price discrimination because the coefficients for the average room rates of grouped hotels and the difference between a hotel's average room rate and the average room rate of neighboring hotels are positive and statistically significant in all the cities. The specific estimates indicate that a traveler's fare on Uber X would increase by $0.19 - $0.90 (0.29% - 2.8%) as the average rate of neighboring hotels within 0.1 mile of each other increases by $100, and a traveler's fare on Uber X would increase by $0.02 - $0.05 (0.03% - 0.16%) for each $100 difference between the average rate of neighboring hotels and the average rate of the hotel

[12] The price increases correspond to percentage increases of 1.71%, 0.25%, and 0.32% per trip. Given the percentage changes are calculated as: (dollar amount/sample mean of the ride fare)*100, where the sample means are $31.61, $64.56, and $31.46 for each city, the percentage increases are greater for shorter distance trips.

where the traveler chooses to stay. The relatively lower magnitude of the coefficients could be explained by the smaller room rate differentials among the matched hotels, which limits the range of the reservation prices of Uber X passengers traveling to those hotels, as compared with the differential among the individual hotels in the full sample. In any case, the finding of price discrimination even among a much narrower range of consumer preferences than in our base case suggests that Uber exploits market segmentation with considerable precision.

<u>Robustness Check: Trip Distance and Time</u>

A priori, it might be expected that Uber X engages in greater price discrimination for longer distance trips and for trips that take more time because it faces less intermodal competition from public transit and hotel and other shuttle services. We therefore conducted a robustness check by expanding the specification in equation (3) to include additional variables that interacted the hotel room rate with route distance and trip duration to explore this possibility. Estimation results from that specification confirmed that the extent of price discrimination varies with route distance and trip duration. However, we also found that including interaction terms in the base specifications caused little change in the average effect of hotel room rates on the Uber X fare in New York, San Francisco, and Los Angeles.

<u>Robustness Check: Supply Shocks</u>

We conducted a robustness check to account for shocks that may affect the supply of drivers at the airport and Uber X fares by including a traveler's wait time in the specification, which is closely related to the number of available drivers. The variable $WaitTime_t$ is the time that an Uber driver takes to arrive at the airport when requested at time *t*. Of course, this variable may be correlated with unmeasured road conditions and correlated with the error term.

A plausible instrument for $WaitTime_t$ is the average time it takes to travel on a section of road near the airport. The New York City Department of Transportation provides traffic information, including real-time traffic speeds and travel times, which are reported directly from traffic sensors installed at every end point of each road segment within the city limits. Figure 4 shows a section of road that provides access to JFK airport. Note that the lane of interest runs in an opposite direction of the hotels in Manhattan, so the average travel time to pass through the section is unrelated to Uber X fares. However, the lane is used in part to enter the airport and the travel time on it affects a passenger's wait time for Uber X. We use the average travel time at time *t* on the section of road indicated in figure 4 as an instrument for $WaitTime_t$ and we estimate the fare regression model for New York by 2SLS. (Los Angeles and San Francisco did not have similar detailed data for traffic conditions on local roads near the airport to enable us to construct instruments for those cities.)

The estimation results shown in table 5 indicate that our basic findings that Uber engages in price discrimination are unaffected when we use travelers' wait time to control for possible shocks at the airport that affect the supply of drivers. In addition, the findings do not appear to be sensitive to whether we instrument wait time. The positive OLS and 2SLS coefficients of wait time, which are statistically significant, indicate that reductions in the supply of drivers that increase waiting times increase Uber X fares, although the effect is much larger when we account for the endogeneity of wait time.

<u>Robustness Check: Frequency of Uber X Observations</u>

We collected data for Uber X every twenty minutes to account for the variation in Uber X fares and operations throughout the day and on different days. The high-frequency data also generated a very large sample. As noted, although the data represent plausible trips that travelers could have taken from a major airport to a hotel, they were not based on actual trips. In practice, trips departing from an airport could occur less frequently, especially outside of peak travel periods during the day and possibly on certain days of the week. We therefore explored whether the findings might be affected if we used a sample based on an hourly frequency of Uber X observations.

Table A1 in the appendix reports estimation results using observations obtained hourly, which we constructed from averages of the twenty-minute frequency observations in hourly blocks. We present parameter estimates for alternative specifications of the Uber X fare, which we have used previously, and the results are similar to the baseline estimates despite the reduction in the frequency of observations. We also explored collecting data for Uber X for a greater trip frequency, every ten minutes, but Uber's API would not allow us to do so.

Robustness Check: Weighting Observations Sampled from Different Times of Day

Market competition faced by Uber varies by time of day. For example, public transportation is largely unavailable after midnight, enabling Uber's pricing power to increase and raising concerns that our findings could be sensitive to the temporal distribution of the trip data. Because we have vehicle trip data between JFK and taxi-zones of NYC, including Uber trips, we conducted a robustness check by estimating a weighted-regression where observations at different times of day were weighted by the share of Uber trips in total vehicle trips. The estimation results presented in appendix table A2 indicate that the magnitudes of the hotel price parameters of interest are slightly smaller than those in the baseline models, but the primary findings regarding Uber's price discrimination behavior are consistent with those obtained from the baseline models.

5. The Welfare Effects of Uber's Price Discrimination Behavior

We have presented robust empirical evidence that Uber X practices third-degree price discrimination for its trips from major airports in Los Angeles, New York, and San Francisco by charging higher fares to travelers who stay at more expensive hotels. The theoretical part of the paper provides intuition by indicating that the welfare effects of third-degree price discrimination are positive based on a variety of functional forms for demand derived from distributions of reservation prices (Cowan (2016)). However, it is not clear whether that conclusion holds for a specific demand curve like a log-linear model, which is likely to be more tractable for empirical work than are more complex functional forms for demand derived from assumed distributions of reservation prices.

Given that the effect of Uber's pricing behavior on travelers' welfare is, in theory, ambiguous, we explore the welfare effects empirically, which also may shed light on additional theoretical possibilities for price discrimination to enhance welfare. We do so by estimating travelers' price elasticity of demand for ridesharing services and by comparing travelers' welfare under discriminatory pricing with their welfare under a uniform price that was imposed to prohibit price discrimination.

The hedonic regressions that we estimated previously were based on fares for hypothetical trips that individual travelers could take from the New York, Los Angeles, and San Francisco airports to their hotels. However, the process we used to generate that data did not allow us to determine the total demand for ridesharing services, which we would need to estimate the demand for ridesharing services. As an alternative data source, we use comprehensive trip records in New York City that are collected by the New York City Taxi & Limousine Commission (TLC) to estimate the demand for ridesharing services. The data include service provided by Uber and Lyft, so the ride-share product types that we include are Uber, Uber carpool, Lyft, and Lyft carpool.

The trip records are measured by New York City taxi zones, which are roughly aligned with Neighborhood Planning Areas. We estimate a ridesharing travel demand model by constructing a panel dataset based on this unit of observation to obtain demand elasticities that vary through an interaction term by the average hotel room rates over the sampled hotels within each taxi zone. Because the price of a ride is likely to be influenced by demand and is therefore endogenous, we estimate the demand model by 2SLS.

The model is specified as:

$$Log(Q_{ikt}) = \phi_0 + \phi_1 \, Log(P_{ikt}) + \phi_2 Log(P_{ikt}) \, \overline{HP}_k + \sum_{i=1}^{I} \omega_i Type_i + \sum_{t=1}^{T} \psi_t Time_t + \sum_{k=1}^{K} \mu_k Zone_k + \epsilon_{ikt}, \tag{5}$$

where Q_{ikt} is the number of trips of ride-share product type *i* traveling to zone *k* at time *t*, P_{ikt} is the fare for the trip of product type *i* traveling to zone *k* at time *t*, $\overline{HP}_k$ is the average hotel price in zone *k*, $Type_i$, $Time_t$, and $Zone_k$ are the ride-share type, time, and zone fixed effects, and ϵ_{ikt} is an error term.[13] We do not include the prices of other transport modes because the (regulated) prices of bus, rail transit, and taxi are fixed conditional on time and zone fixed-effects. We include $\overline{HP}_k$ in the demand function to estimate a heterogeneous price elasticity that varies by trip destination *k*. As noted, we use a log-linear functional form because of its empirical tractability.[14]

To account for the potential endogeneity that arises from the relationship between Q_{ikt} and P_{ikt}, we construct instruments for P_{ikt} based on exogenous cost variables—trip distance, duration per mile, and real-time average traffic speeds for the borough where each destination zone is located—which are determined by the destination that the traveler arriving at the airport has predetermined. Rideshare companies' profit-maximizing pricing decisions are influenced by those

[13] The fare data are the same fare data that we used previously. Thus, we again assume that the ride-share product types Uber and Lyft charge the same prices, which is plausible. We also assume that the other Uber and Lyft services also charge those prices, which is possible. The assumption limits the variation in ride-share prices; however, we find that the effect of prices on demand is estimated with statistical precision.

[14] We do not know Uber's costs, which could be used to construct a profit function from which we could derive a log-linear demand function that is consistent with profit maximizing behavior. For our purposes, it is worth pointing out that Uber's costs should not be affected by whether it sets a uniform price or continues to set discriminatory prices.

time-varying cost differences across taxi zones and times but random-shocks, such as traffic accidents, affecting the demand for ridesharing services are unlikely to be correlated with, for example, congestion conditional on time and zone fixed-effects. As noted, such fixed effects include the availability of alternative transport modes.[15]

The estimated coefficients for the first stage of the 2SLS estimation, presented in table 6, indicate that all the instruments have a statistically significant effect on price and the high R-squares suggest that the instruments are not weak.[16] As a robustness check in columns (3) and (4) of the table, we use 60 minutes instead of 20 minutes as our unit of time by grouping data from different time intervals.

We present OLS and 2SLS estimates of the demand model in table 7. The estimated coefficients have plausible signs and are statistically and economically significant. As shown in columns (1) and (2), travelers' demand for ridesharing services is inversely related to price, while travelers' sensitivities to price decrease as average hotel prices increase, indicating that they have heterogeneous preferences that ridesharing companies cater to with price discrimination. As shown in columns (3) and (4), the estimation results are not sensitive to using a longer unit of time to generate the observations. Based on the 2SLS coefficients in columns (2) and (4), we calculate that the price elasticity of demand (at the mean of $\overline{HP}_k$) is -0.065 and -0.152, respectively, although the difference is not statistically significant. The inelastic demand elasticity estimates are plausible

[15] Shocks to congestion are exogenous because fluctuations in demand for ride-share services are unlikely to affect congestion in a specific zone conditional on time fixed-effects. However, real-time pricing algorithms of ride-share services adjust their prices to take random shocks into account. It would take an abnormal amount of congestion delay to cause travelers to shift away from ridesharing, which would affect demand. We assume that such congestion delay rarely occurs.

[16] Although, for example, the coefficients for distance and duration in tables 3 and table 6 are different, the main reason for the differences is likely because we specify different fixed effects in the models. That is, zone fixed effects may also capture the effect of distance and duration on price.

and broadly consistent with elasticity estimates of other urban transportation services (Small and Verhoef (2007), Winston (2013)).

We use the 2SLS coefficients to estimate consumers' surplus under price discrimination and under uniform pricing to assess the welfare effects of price discrimination. The discriminatory and uniform prices are computed using the estimated pricing equation presented in column 4 of Table 7.[17] We predict the discriminatory prices by using the observed hotel room rates and the average room rate, respectively, as specified in the equation, and we predict the uniform prices by setting the hotel room rates equal to the average room rate. The impact on consumer welfare (ΔCS) caused by price discrimination in zone *k* at time *t* is calculated as:

$$\Delta CS \;=\; \int_{P_{Disc}}^{P_{Unif}} f(P)\, dP \qquad (6)$$

where P_{Unif} is the uniform price; P_{Disc} is the discriminatory price; and $f(P) = P^{\widehat{\Phi_1} + \widehat{\Phi_2}\,\overline{HP}_k}$ is the demand function constructed from the demand estimation results.

The results of the calculation summarized in table 8 are that price discrimination increases consumer surplus for about 75 percent of the trips in the sample. Travelers obtain a welfare gain, on average, that approaches \$0.01 per trip for a modest aggregate annual welfare gain of roughly \$1.5 million, and the welfare estimates are robust to different sampling frequencies of the data.[18] Because different types of travelers take trips to different hotels, the welfare effects of price discrimination are positive for some travelers and negative for others, depending on their destination. The aggregate consumer surplus change, therefore, could be small because those effects offset each other.

[17] The pricing equation, which we use to compute the discriminatory and uniform prices, is a reduced form approximation of Uber's optimal pricing rule.

[18] Castillo (2020) finds that surge pricing increases travelers' welfare relative to uniform pricing.

In terms of welfare effects, the major benefit of price discrimination, which merits more attention than the pricing gain and is undoubtedly greater than $1.5 million, is that it expands travelers' hotel options at the destination by matching heterogenous demand for and supply of rideshare services. For example, lower rideshare fares to hotels with low room rates enable travelers to stay at those hotels when their next best option may have been to use a shuttle bus and stay at a more expensive hotel. As noted, ridesharing companies are willing to offer lower fares as a "reward" to increase traffic and the use of drivers' vehicles on less popular routes.

6. Conclusions

Price discrimination by firms may enhance consumer welfare by giving consumers greater opportunities to purchase goods and services, which are aligned with their preferences. However, economic theory is ambiguous about the welfare effects of third-degree price discrimination, which occurs when consumers in different markets are charged different prices for the same good or service.

We have used price data for hypothetical trips provided by Uber, which align closely with the prices that travelers would have paid if they had actually taken those trips, to test for the existence of price discrimination in different markets, defined by the same airport origin and different hotel destinations. We have obtained robust findings that travelers staying at more expensive hotels pay higher fares, all else equal, than travelers staying at less expensive hotels pay. Importantly, we also have found that discriminatory fares improve travelers' welfare compared with a uniform fare that could be mandated by a regulatory authority to prohibit price discrimination. We suggested that discriminatory fares in rideshare markets benefit rideshare companies and travelers by expanding travel options for travelers and by increasing utilization of drivers' vehicles.

It is, of course, incautious to generalize from our findings about the welfare effects of third-degree price discrimination in certain urban transportation markets. At the same time, the findings may suggest other markets where the practice is likely to enhance consumer welfare and should not be prevented by antitrust or regulatory authorities.

References

Aguirre, I. S. Cowan, and J. Vickers. 2010. "Monopoly price discrimination and demand curvature," *American Economic Review*, vol. 100, no. 4, pp. 1601–15.

Borenstein, Severin and Nancy L. Rose, "Competition and price dispersion in the us airline industry," *Journal of Political Economy*, vol. 102, no. 4, pp. 653–683, 1994.

Carlton, Dennis W. and Ken Heyer. 2008. "Extraction vs. Extension: The Basis for Formulating Antitrust Policy towards Single-Firm Conduct," *Competition Policy International*, volume 4, pp. 285-305.

Carlton, Dennis W. and Michael Waldman. 2014. "Robert Bork's Contribution's to Antitrust Perspectives on Tying Behavior," *Journal of Law and Economics*, volume 57, August, pp. S121-S144.

Castillo, Juan Camilio. 2020. "Who Benefits from Surge Pricing?," Stanford Job Market Paper, October.

Cohen, P., R. Hahn, J. Hall, S. Levitt, and R. Metcalfe, "Using big data to estimate consumer surplus: The case of uber," *National Bureau of Economic Research*, 2016.

Corts, Kenneth S. 1998. "Third-degree price discrimination in oligopoly: all-out competition and strategic commitment," *The RAND Journal of Economics*, pp. 306–323, 1998.

Cowan, S. 2016. "Welfare-increasing third-degree price discrimination," *The RAND Journal of Economics*, vol. 47, no. 2, pp. 326–340.

Cowan, S. 2012. "Third-degree price discrimination and consumer surplus," *The Journal of Industrial Economics*, vol. 60, no. 2, pp. 333–345.

Gerardi, Kristopher S. and Adam Hale Shapiro. 2009. "Does Competition Reduce Price Dispersion? New Evidence from the Airline Industry," *Journal of Political Economy*, volume 117, February, pp. 1-37.

Holmes, Thomas J. 1989. "The effects of third-degree price discrimination in oligopoly," *American Economic Review*, vol. 79, no. 1, pp. 244–250.

Hwang, Hyeonjun, Clifford Winston, and Jia Yan. 2021. "Measuring the Benefits of Ridesharing Services to Urban Travelers: The Case of the San Francisco Bay Area," Brookings Institution working paper, January.

Johnson, JP and D. P. Myatt. 2006. "On the simple economics of advertising, marketing, and product design," *American Economic Review*, vol. 96, no. 3, pp. 756–784.

Luttmann, A. 2019. "Evidence of directional price discrimination in the us airline industry," *International Journal of Industrial Organization*, vol. 62, pp. 291–329.

Morrison, Steven A. and Clifford Winston. 1995. *The Evolution of the Airline Industry*, Brookings Institution, Washington, D.C.

Nahata, B., K. Ostaszewski, and P. K. Sahoo. 1990. "Direction of price changes in third-degree price discrimination," *American Economic Review*, vol. 80, no. 5, pp. 1254–1258.

Nevo, Aviv and Catherine Wolfram. 2002. "Why Do Manufacturers Issue Coupons? An Empirical Analysis of Breakfast Cereals," *RAND Journal of Economics*, vol. 33, no. 2, pp. 319-339.

Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, volume 82, no. 1, pp. 34-55.

Schmalensee, Richard. 1981. "Output and welfare implications of monopolistic third-degree price discrimination," *American Economic Review*, vol. 71, pp. 242–247, 1981.

Shepard, Andrea. 1991. "Price discrimination and retail configuration," *Journal of Political Economy*, vol. 99, no. 1, pp. 30–53.

Tirole, Jean.1988. *The Theory of Industrial Organization*, MIT Press, Cambridge, Massachusetts.

Varian, Hal. 1985. "Price discrimination and social welfare," *American Economic Review*, vol. 75, no. 4, pp. 870–875.

Winston, Clifford. "On the Performance of the U.S. Transportation System: Caution Ahead," *Journal of Economic Literature*, vol. 51, no. 3, pp. 773-824.

Exhibit 1. Post About Discriminatory Uber Fares

Tripadvisor

Forum / United States / Hawaii / Oahu

Uber - mark up if hotel is selected

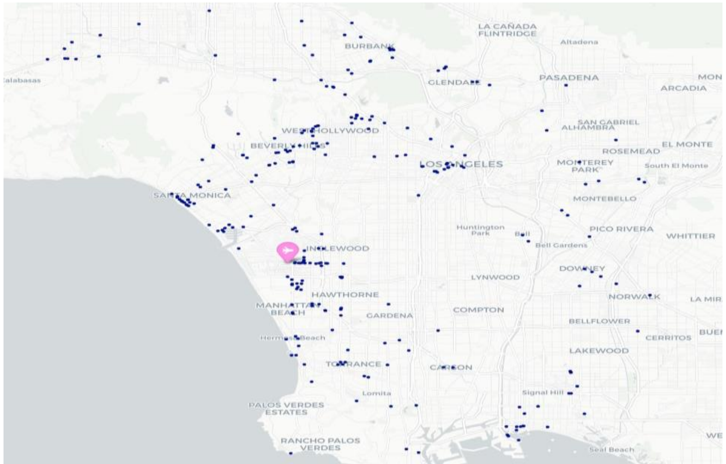
SimplyHuman · 1,512 forum posts
New York
Aug 18, 2021, 1:40 PM

I noticed a huge difference in price when my hotel is selected as opposed to picking an address right next to the hotel. As an example, Hyatt Regency to USS Arizona $50, but using an address just outside the hotel, $33. Same date, same time. this is just one example. This begs the question if Uber is building in a premium in its rates for hotel locations. I do understand that Uber has other pricing variable such as date and time of day, cab availability etc. my question is whether they are also using “hotel location” as a variable for pricing.

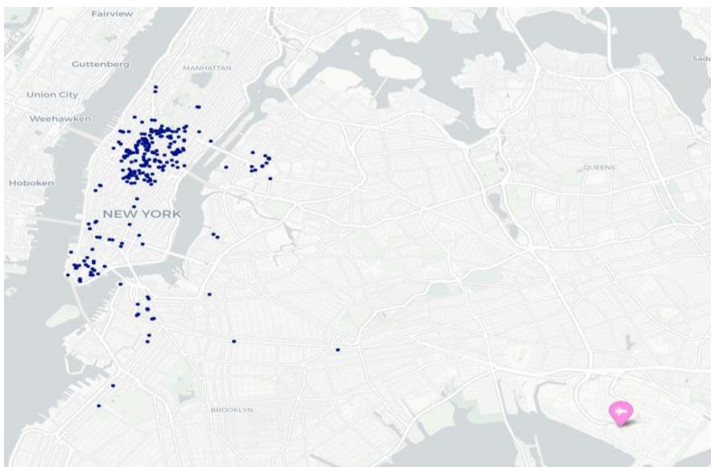
Reply

Figure 1. Airports and the Locations of Hotels in the Sample

(a) LAX



(b) JFK



(c) SFO

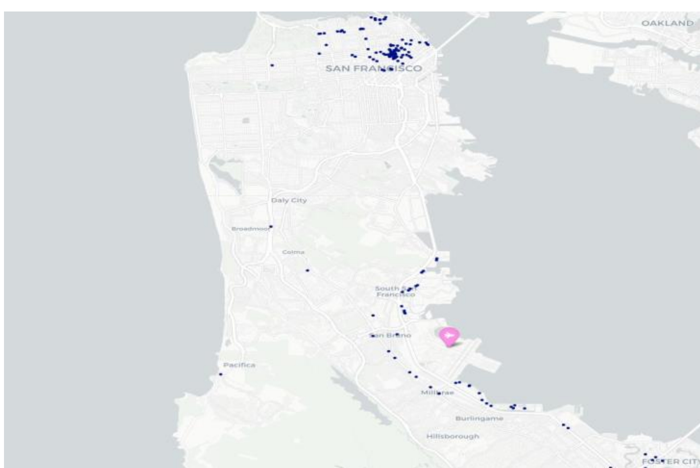
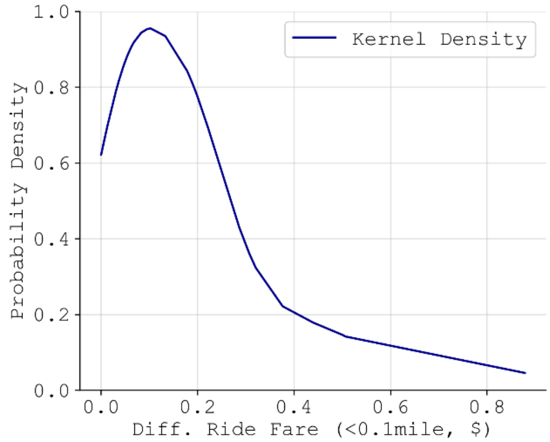
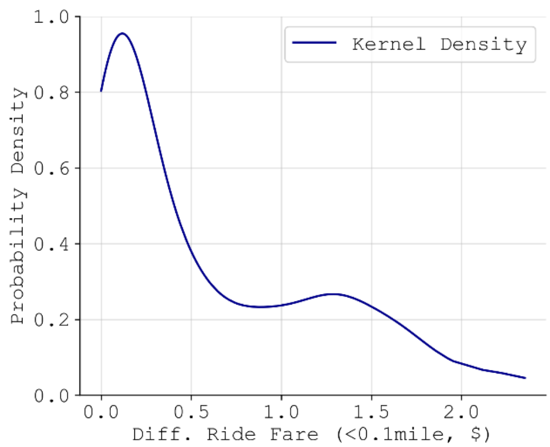


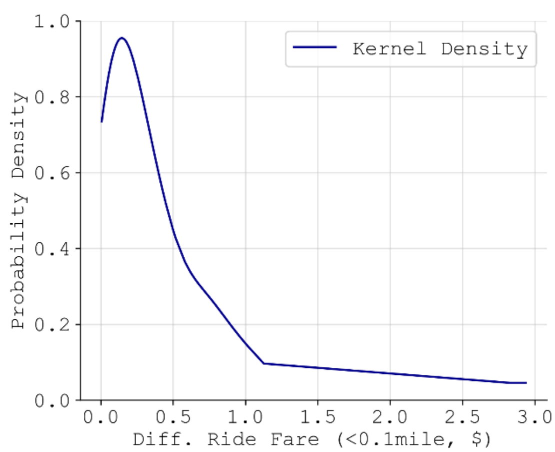
Figure 2. Distribution of fare differences between matched route pairs



(a) LAX



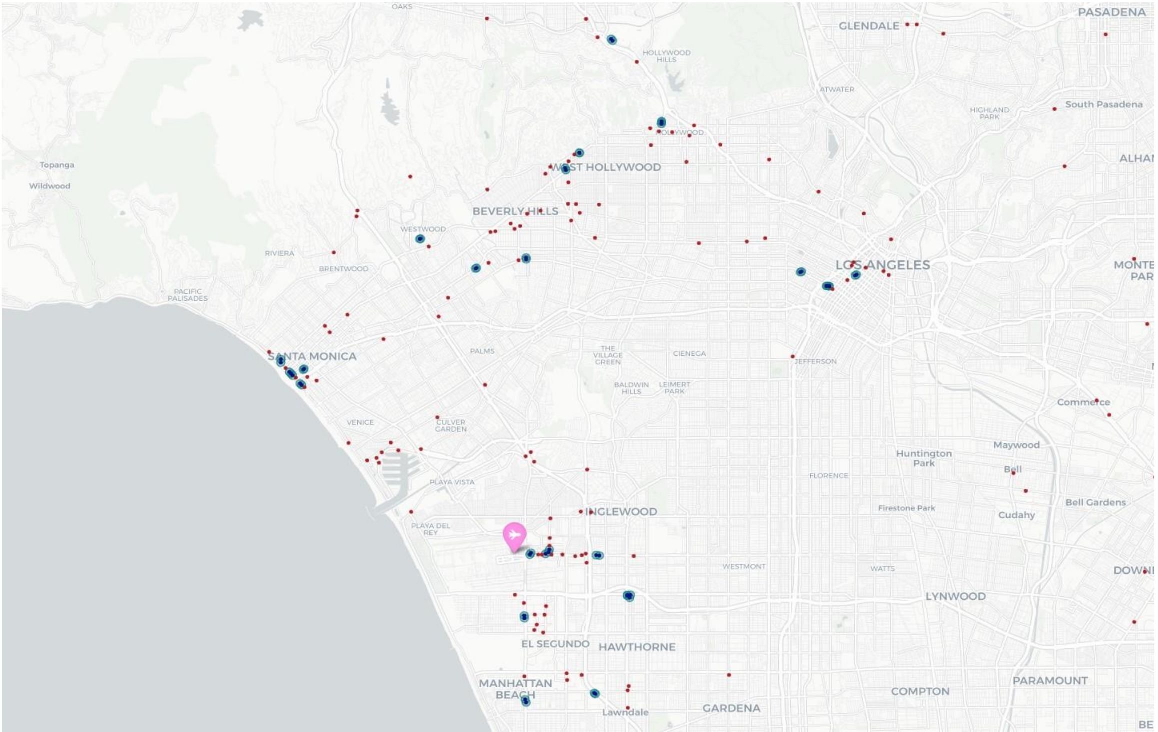
(b) JFK



(c) SFO

Figure 3. Locations of Geographically Matched Hotels

(a) LAX



(b) JFK

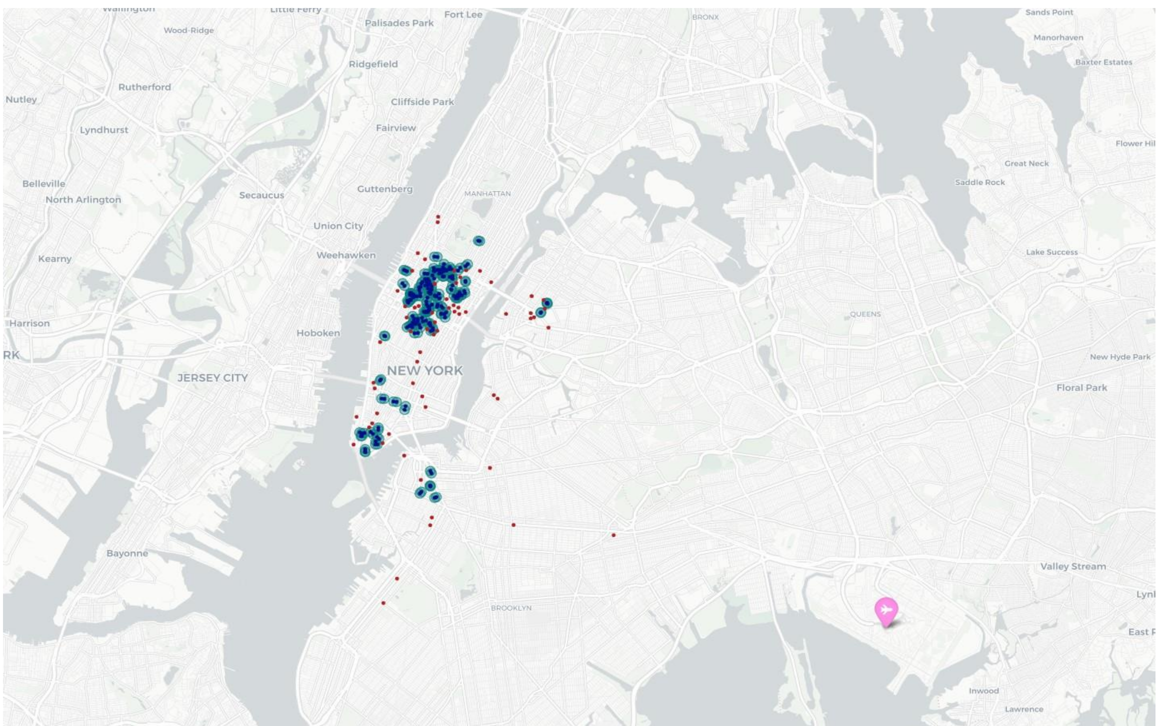


Figure 3 continued. Locations of Geographically Matched Hotels

(c) SFO

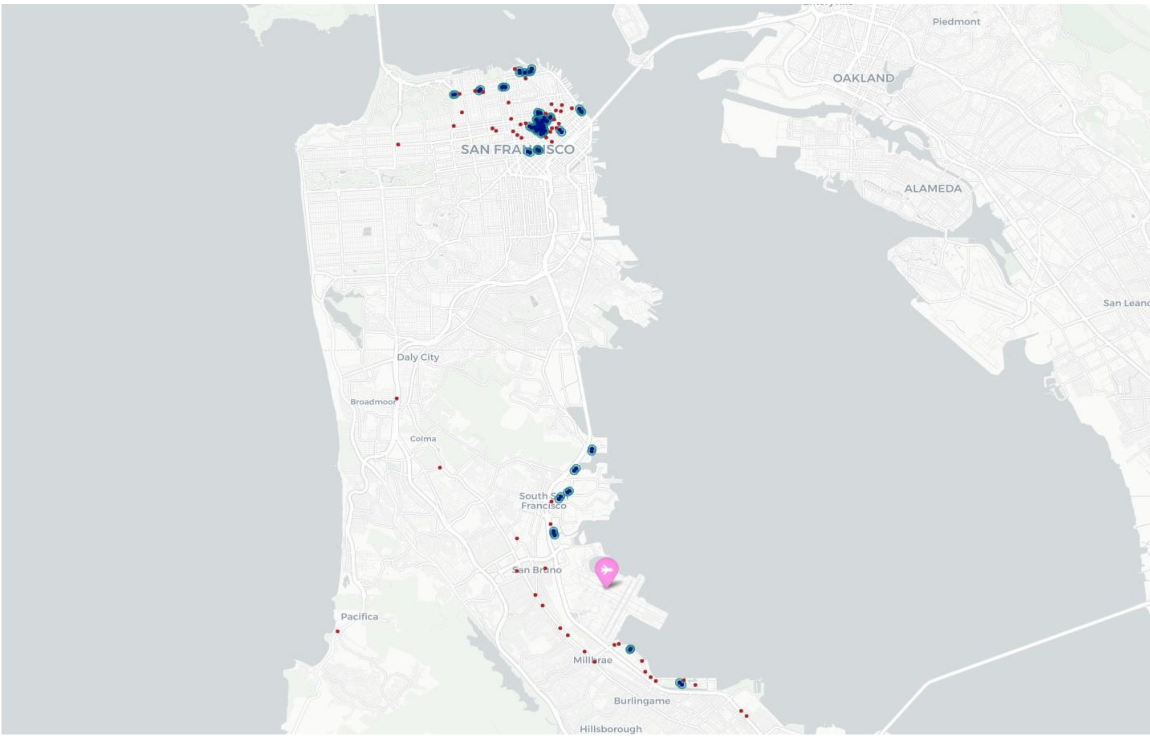


Figure 4. Location of Traffic Sensors On A Road Section Leading To JFK Airport

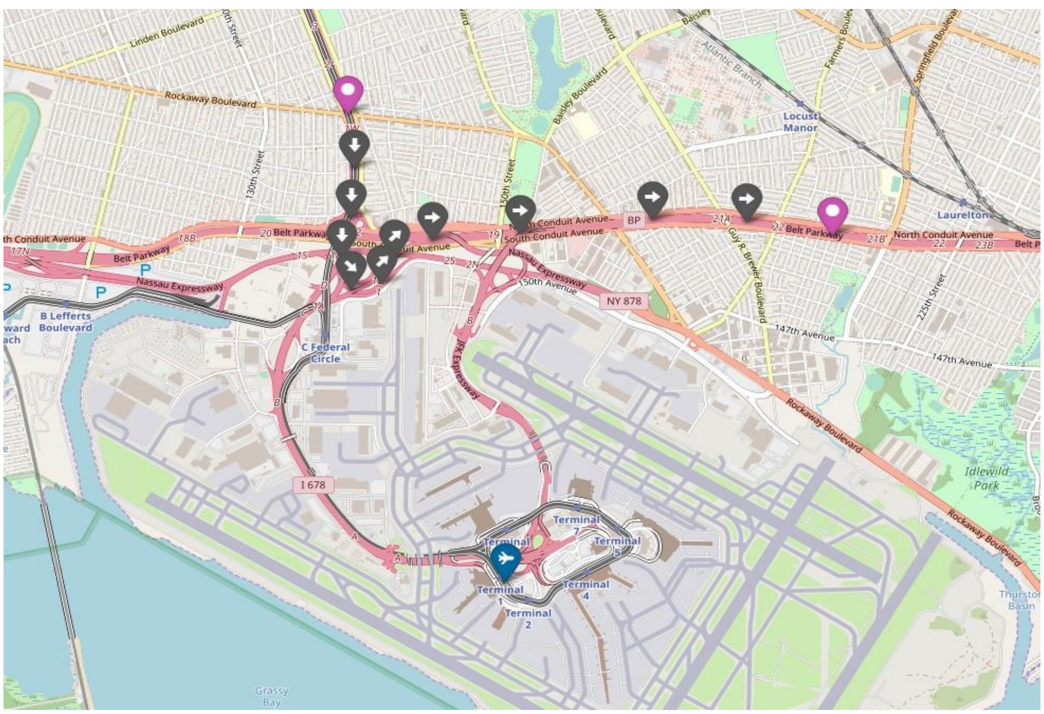


Table 1. Summary statistics: Ride fare and characteristics of UberX and hotel rate by city

	City		
	Los Angeles	New York	San Francisco
	(1)	(2)	(3)
	A. Ride fare and characteristics		
Ride fare ($)	31.61	64.56	31.46
	(15.58)	(9.14)	(10.08)
Distance (mile)	15.34	18.56	12.00
	(8.41)	(2.53)	(5.02)
Duration per trip (min)	31.62	45.70	21.49
	(14.89)	(12.00)	(10.02)
Duration per mile (min)	2.43	2.49	1.86
	(0.96)	(0.68)	(0.47)
Wait Time (min)	4.50	3.20	2.58
	(2.32)	(1.24)	(1.40)
Observations	1582694	1510151	928785
	B. Hotel room rate		
Room rate ($)	218.45	336.05	336.15
	(119.80)	(150.85)	(191.16)
Observations	261	242	152

[1] The entry in each cell is the mean. Standard deviations are in parentheses.

Table 2. Summary statistics: Matched neighboring hotels

	Los Angeles	New York	San Francisco
	(1)	(2)	(3)
The number of neighboring hotels within each group	2.35	4.04	3.85
	(0.67)	(2.20)	(2.38)
Average room rate of grouped neighboring hotels	244.88	349.14	338.62
($LocHP$, $)	(86.63)	(121.98)	(103.07)
Difference between hotel j's rate and average	0.43	-3.75	7.07
room rate of neighboring hotels ($DLocHP$, $)	(63.62)	(156.75)	(134.39)
The number of hotels chosen as neighbor	55	202	78

[1] Hotel j is chosen as a neighbor of hotel k if hotel j is within 0.1-mile radius of hotel k.
[2] The entry in each cell is the mean. Standard deviations are in parentheses.

Table 3. Route-Based Fare Discrimination Parameter Estimates

Dep. Var. P_{jt}	Los Angeles		New York		San Francisco	
	(1)	(2)	(3)	(4)	(5)	(6)
$HighHP$	1.0296***		0.848***		0.6311***	
	(0.0141)		(0.0086)		(0.0122)	
HP		0.0054***		0.0016***		0.001***
		(0.0001)		(0.0000)		(0.0000)
$Distance$	1.6029***	1.6069***	2.602***	2.6133***	1.8196***	1.8386***
	(0.0015)	(0.0015)	(0.0023)	(0.0023)	(0.0013)	(0.0012)
$Duration$	1.7806***	1.7888***	7.8456***	7.8553***	2.4870***	2.5079***
	(0.0118)	(0.0118)	(0.0121)	(0.0121)	(0.0116)	(0.0115)
Constant	5.7304***	4.9801***	-4.3292***	-4.6928***	7.0925***	6.8309***
	(0.0591)	(0.0596)	(0.0558)	(0.0565)	(0.049)	(0.0487)
Observations	1582694	1582694	1510151	1510151	928785	928785

[1] Coefficients of time fixed effects are omitted.
[2] Robust standard errors are in parentheses.
[3] *** Significant at the 1% level.

Table 4: Route-based Geographic Matching Fare Discrimination Parameter Estimates

Dep. Var. P_{jt}	Los Angeles		New York		San Francisco	
	(1)	(2)	(3)	(4)	(5)	(6)
$LocHP$	0.009***	0.0089***	0.0019***	0.0019***	0.0053***	0.0053***
	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
$DLocHP$		0.0005***		0.0002***		0.0002***
		(0.0002)		(0.0000)		(0.0001)
$Distance$	1.5724***	1.5724***	2.4585***	2.4585***	1.8471***	1.8471***
	(0.0034)	(0.0034)	(0.0028)	(0.0028)	(0.0016)	(0.0016)
$Duration$	1.4187***	1.4173***	7.3972	7.3978***	2.4459***	2.4460***
	(0.0221)	(0.0221)	(0.014)	(0.014)	(0.0172)	(0.0172)
Constant	4.6825***	4.6857***	-0.752***	-0.7684***	5.5206***	5.5187***
	(0.1159)	(0.116)	(0.0689)	(0.069)	(0.0694)	(0.0694)
Observations	333522	333522	1164502	1164502	476627	476627

[1] Coefficients of time fixed effects are omitted.
[2] Robust standard errors are in parentheses.
[3] *** Significant at the 1% level.

Table 5. Route-Based Fare Discrimination OLS and 2SLS Parameter Estimates for New York

Dep. Var. P_{jt}		OLS			2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
$HighHP$	0.8491***			0.8468***		
	(0.0087)			(0.009)		
HP		0.0016***			0.0016***	
		(0.0000)			(0.0000)	
$LocHP$			0.0019***			0.0019***
			(0.0000)			(0.0000)
$DLocHP$			0.0002***			0.0002***
			(0.0000)			(0.0000)
$Distance$	2.5995***	2.6107***	2.4557***	2.6046***	2.6158***	2.4614***
	(0.0023)	(0.0023)	(0.0029)	(0.0025)	(0.0025)	(0.0031)
$Duration$	7.8344***	7.8440***	7.3903***	7.8606***	7.8701***	7.4212***
	(0.0122)	(0.0122)	(0.0141)	(0.0129)	(0.0129)	(0.015)
$WaitTime$	0.2269***	0.2272***	0.2238***	1.6660***	1.6661***	1.7092***
	(0.0055)	(0.0055)	(0.0061)	(0.2532)	(0.2534)	(0.2862)
Constant	-4.9348***	-5.3000***	-1.3681***	-9.7133***	-10.077***	-6.3195***
	(0.0597)	(0.0604)	(0.0731)	(0.8416)	(0.8424)	(0.9546)
Observations	1482233	1482233	1143168	1482233	1482233	1143168

[1] Coefficients of time fixed-effects are omitted.
[2] Robust standard errors are in parentheses.
[3] *** Significant at the 1% level.

Table 6. First-Stage Estimates of Rideshare Demand

	$Log(P_{ikt})$ (20min. frequency) (1)	$Log(P_{ikt})\,\overline{HP}_k$ (20min. frequency) (2)	$Log(P_{ikt})$ (60min. frequency) (3)	$Log(P_{ikt})\,\overline{HP}_k$ (60min. frequency) (4)
$Distance$	0.0251***	8.7748***	0.0253***	8.7688***
	(0.0001)	(0.0776)	(0.0002)	(0.0934)
$Duration$	0.0151***	5.7574***	0.0157***	6.0481***
	(0.0005)	(0.2139)	(0.0006)	(0.2624)
$Speed$	-0.0011***	-0.301***	-0.0008***	-0.1832***
	(0.0001)	(0.0363)	(0.0001)	(0.042)
Constant	3.6175***	1130.235***	3.6055***	1128.17***
	(0.0059)	(2.4505)	(0.007)	(2.9386)
R^2	0.8662	0.9944	0.8825	0.9943
Observations	122,907	122,907	88,185	88,185

[1] Coefficients of product type, time, and zone fixed effects are not shown.
[2] Robust standard errors are in parentheses.
[3] *** Significant at the 1% level.

Table 7. OLS and 2SLS Rideshare Demand Parameter Estimates

Dep.Var. $Log(Q_{ikt})$	OLS (20min. frequency) (1)	2SLS (20min. frequency) (2)	OLS (60min. frequency) (3)	2SLS (60min. frequency) (4)
$Log(P_{ikt})$	-0.0525***	-4.7257***	-0.1806***	-4.7044***
	(0.0201)	(1.2379)	(0.0304)	(1.4215)
$Log(P_{ikt})\,\overline{HP}_k$	0.0002***	0.0138***	0.0006***	0.0136***
	(0.0000)	(0.0036)	(0.0001)	(0.0041)
Constant	-0.16133***	-16.8702***	-0.2023***	8.6951***
	(0.0461)	(4.2273)	(0.0709)	(2.8268)
Observations	125,046	122,907	89,698	88,185

[1] Coefficients of product type, time, and zone fixed effects are not shown.
[2] Robust standard errors are in parentheses.
[3] *** Significant at the 1% level.

Table 8. Consumer Welfare Impacts of Price Discrimination[1]

	20 min. frequency (1)	Hourly frequency (2)
Proportion of $+\Delta CS$	74.5%	75.4%
ΔCS ($)	+0.0088 (0.0001)	+0.0071 (0.0001)

[1] Each element in the second and third columns shows the difference in consumer surplus between price discrimination and uniform pricing. The + indicates that consumer surplus increases when price discrimination is adopted. Standard errors in parentheses were calculated by using the bootstrap where we used the estimated coefficients and conducted random sampling from the trip record data (with replacement).

Appendix

Table A1. Route-Based Fare Discrimination Parameter Estimates Based on Hourly Observations

Dep. Var. P_{jt}	Los Angeles			New York			San Francisco		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$HighHP$	1.0258***			0.7932***			0.6257***		
	(0.0182)			(0.0125)			(0.016)		
HP		0.0054***			0.0015***			0.0009***	
		(0.0001)			(0.0000)			(0.0000)	
$LocHP$			0.0088***			0.0018***			0.0052***
			(0.0002)			(0.0001)			(0.0001)
$DLocHP$			0.0005*			0.0002***			0.0002***
			(0.0003)			(0.0000)			(0.0001)
$Distance$	1.6009***	1.6050***	1.5723***	2.7233***	2.7362***	2.585***	1.8202***	1.8392***	1.8479***
	(0.002)	(0.002)	(0.0045)	(0.0035)	(0.0036)	(0.0044)	(0.0018)	(0.0016)	(0.0021)
$Duration$	1.7274***	1.7360***	1.3609***	8.2341***	8.2417***	7.8214***	2.4582***	2.4796***	2.3712***
	(0.0164)	(0.0163)	(0.0312)	(0.0186)	(0.0187)	(0.0214)	(0.0163)	(0.0162)	(0.0243)
Constant	5.8218***	5.0681***	4.8102***	-7.1948***	-7.5628***	-3.7957***	7.0825***	6.8208***	5.5871***
	(0.0752)	(0.0757)	(0.1512)	(0.0838)	(0.0851)	(0.105)	(0.0654)	(0.0649)	(0.0922)
Observations	537382	537382	113238	509509	509509	392774	316004	316004	162160

[1] Coefficients of time fixed effects are omitted.

[2] Robust standard errors are in parentheses.

[3] *** Significant at the 1% level.

Table A2. Weighted-regression estimates of route-based price discrimination parameters (NY)

Dep. Var. P_{jt}	(1)	(2)	(3)
$HighHP$	0.7544***		
	(0.01)		
HP		0.0012***	
		(0.0000)	
$LocHP$			0.0011***
			(0.0001)
$DLocHP$			0.0001***
			(0.0000)
$Distance$	2.6153***	2.6265***	2.4788***
	(0.0026)	(0.0026)	(0.0032)
$Duration$	7.3624***	7.3789***	6.8401***
	(0.0134)	(0.0135)	(0.0158)
Constant	-3.8073***	-4.0929***	-0.052***
	(0.0615)	(0.0623)	(0.078)
Observations	1582694	1510151	928785

[1] Coefficients of time fixed effects are omitted.
[2] Robust standard errors are in parentheses.
[3] *** Significant at the 1% level.