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Abstract

We use Uber fare data for passenger trips from Los Angeles, New York, and San Francisco 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 ride-sharing companies to price discriminate improves travelers' welfare, on average, by increasing their travel options.

1. Introduction

Price discrimination by firms—the practice of charging consumers on the basis of 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; 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; Luttmann 2019).

Because ride-sharing 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, ride-sharing 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 ride-sharing company in the world,

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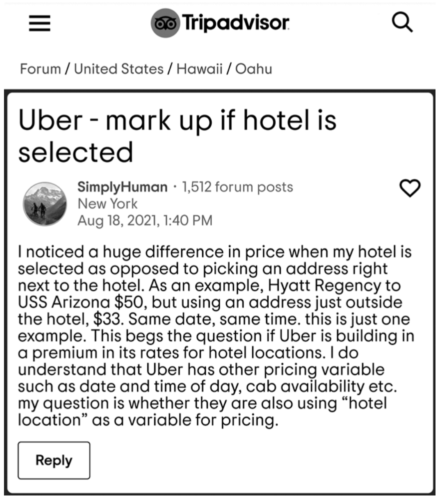

Figure 1. Post about discriminatory Uber fares

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 on the basis of travelers' destinations, which we argue is a form of third-degree price discrimination.[2] Anecdotal evidence presented in Figure 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; we use the extensive fare data generated by UberX for trips originating from the major airports in Los Angeles, San Francisco, and New York to hotels in those metropolitan areas.[3] UberX fare data are attractive for this purpose because the origin of a trip is clearly indicated, which enables 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

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

[2] Carson (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. Uber's other services include UberXL and UberBlack, featuring sport utility vehicles 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.

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

with lower average room rates; we hypothesize that the latter travelers will be charged lower UberX fares because they have signaled that they are likely to have lower reservation prices for their local transportation.

To test the hypothesis, we randomly selected 700 trips that originated at Los Angeles International Airport, John F. Kennedy International Airport, and San Francisco International Airport and terminated at hotels located within a 20-mile radius of each airport. We group the hotels into zones with a .1-mile radius. We collected high-frequency data (every 20 minutes) for UberX trips, including fares, estimated travel time of the trip (duration), and distance, on those routes from September 1, 2018, to November 30, 2018. Data collection is an automated process that uses Uber's open application programming interface (API) 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 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 $.10 to $.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 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 ride-sharing's third-degree discriminatory fare structure in the transportation market composed of New York's John F. Kennedy International 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 ride-sharing 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.

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] As-

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

[5] The fare increases correspond to a .25–1.7 percent 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) $\times$ 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 trips.

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

sume that 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. The term $\overline{p}$ is a uniform price that does not vary by market.

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 application, then Uber offers the traveler a fare for that trip, and if the traveler's reservation price is lower than the offered fare, she will reject the offer. Conversely, if her reservation price is higher than or equal to the offered fare, she will accept the offer. Given the information generated by repeated interactions between Uber and 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 in which the corresponding inverse demand function for market i is given by $p_i(Q_i) = \theta_i - \sigma \ln[(Q_i/n_i)/(1 - Q_i/n_i)]$. This leads to proposition 1, in which 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 char-

[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.

acterized by consumers' inverse demand functions derived from a logistic distribution of reservation prices, then there exist profit-maximizing discriminatory prices $p_{\mathrm{A}}^{\star}$ and $p_{\mathrm{B}}^{\star}$, such that the uniform price $\overline{p}^{\star}$, which maximizes the firm's profit, lies between the discriminatory prices $p_{\mathrm{A}}^{\star}$ and $p_{\mathrm{B}}^{\star}$ ($\overline{p}^{\star} \in [p_{\mathrm{A}}^{\star}, p_{\mathrm{B}}^{\star}]$).

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 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 $Q_i^{\star}$ that maximizes profit from markets A and B. Cowan (2016) argues that only one profit-maximizing price exists because of the unique interior solution $Q_i^{\star}$ and because demand is downward sloping, which implies that the condition in theorem 1 of Nahata, Ostaszewski, and Sahoo (1990) holds.

With regard 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, proposition 2 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 (1985) uses welfare bounds to identify the change in social welfare from the change from uniform pricing to third-degree price discrimination:

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

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

Cowan (2016) proves that the following equality holds: $(p_i - c_{\mathrm{UB}})\Delta Q_i + \sigma n_i \pi_i'(\overline{p}) = (1 - \overline{q}_i) n_i [\pi_i(p_i) - \pi_i(\overline{p})]$, where $\overline{q}_i = q_i(\overline{p})$ and $\pi_i(p)$ is the profit obtained from market i given price p. Thus, the term of interest, $\Sigma_i(p_i - c_{\mathrm{UB}})\Delta Q_i$, satisfies the following equality:

$$\begin{aligned}\sum_i (p_i - c_{\mathrm{UB}})\Delta Q_i &= \sum_i n_i\{(1 - \overline{q}_i)[\pi_i(p_i) - \pi_i(\overline{p})] - \sigma\pi_i'(\overline{p})\} \\ &= \sum_i (1 - \overline{q}_i) n_i [\pi_i(p_i) - \pi_i(\overline{p})]\end{aligned} \tag{2}$$

because $\Sigma_i n_i \pi_i'(\overline{p}) = 0$, which is the first-order condition for profit maximization under uniform pricing. Given $1 - \overline{q}_i > 0$, $n_i > 0$, and $\pi_i(p_i) - \pi_i(\overline{p}) \geq 0$ by theorem 1 of Nahata, Ostaszewski, and Sahoo (1990), then $\Sigma_i (1 - \overline{q}_i) n_i [\pi_i(p_i) - \pi_i(\overline{p})] > 0$, 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, which decreases 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 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

[8] Cowan (2016) proves that the necessary condition of Varian (1985), which is the left-hand-side inequality in expression (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 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.

and to be offered higher fares for trips on UberX. Uber is likely to know the distribution of travelers' reservation prices on the basis of 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 UberX fares.

We obtain a consistent estimate of this relationship by controlling for other important influences on UberX 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 .1-mile radius. We also control for the primary trip characteristics, route distance and duration, which are likely to affect UberX'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 used route-based pricing since at least 2017.[10]

3.1. Data

We compile an extensive data set using Uber's API that contains the fare, distance, duration, and wait time for the arrival of UberX 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 data were collected every 20 minutes from September 1, 2018, to November 30, 2018, for roughly 700 routes that originated at Los Angeles International Airport, John F. Kennedy International Airport, and San Francisco International Airport and that terminated at hotels within a 20-mile radius of each airport. It is possible that Uber could identify the exact location of travelers using global positioning system software to set fares that discriminate on the basis of 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 the airport as the only origin.

We obtain 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 facili-

[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.

ties, and level of services offered by the property. We used the AAA ratings information to confirm the relationship between hotel room rates and quality; that is, travelers pay higher room rates to stay at higher-quality hotels. Figure 2 identifies the location of each airport and the hotels within 20 miles of it that are included in the sample. Most of the hotels in New York are in Manhattan; thus, the UberX trips in New York take longer and are farther than the UberX trips in San Francisco and Los Angeles because most of the hotels in those California markets are closer to airports.

Table 1 presents summary statistics for the fares, trip characteristics, and hotel room rates for each airport in the sample. Consistent with Figure 2, the longest, most time-consuming, and therefore most expensive UberX 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 are a greater distance. We speculate that this may reflect the fact that public transit is a more competitive option for travelers in airport-to-hotel transportation markets in San Francisco than in Los Angeles. For example, the Bay Area Rapid Transit System has a station at the San Francisco Airport from which 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 suggests 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 UberX 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 UberX trips and the supply of drivers.

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

3.2. *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 for which destination hotels are less than .1 mile 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 3. The graphs suggest that Uber uses hotel characteristics as inputs to design a route-based pricing algorithm: 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.

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

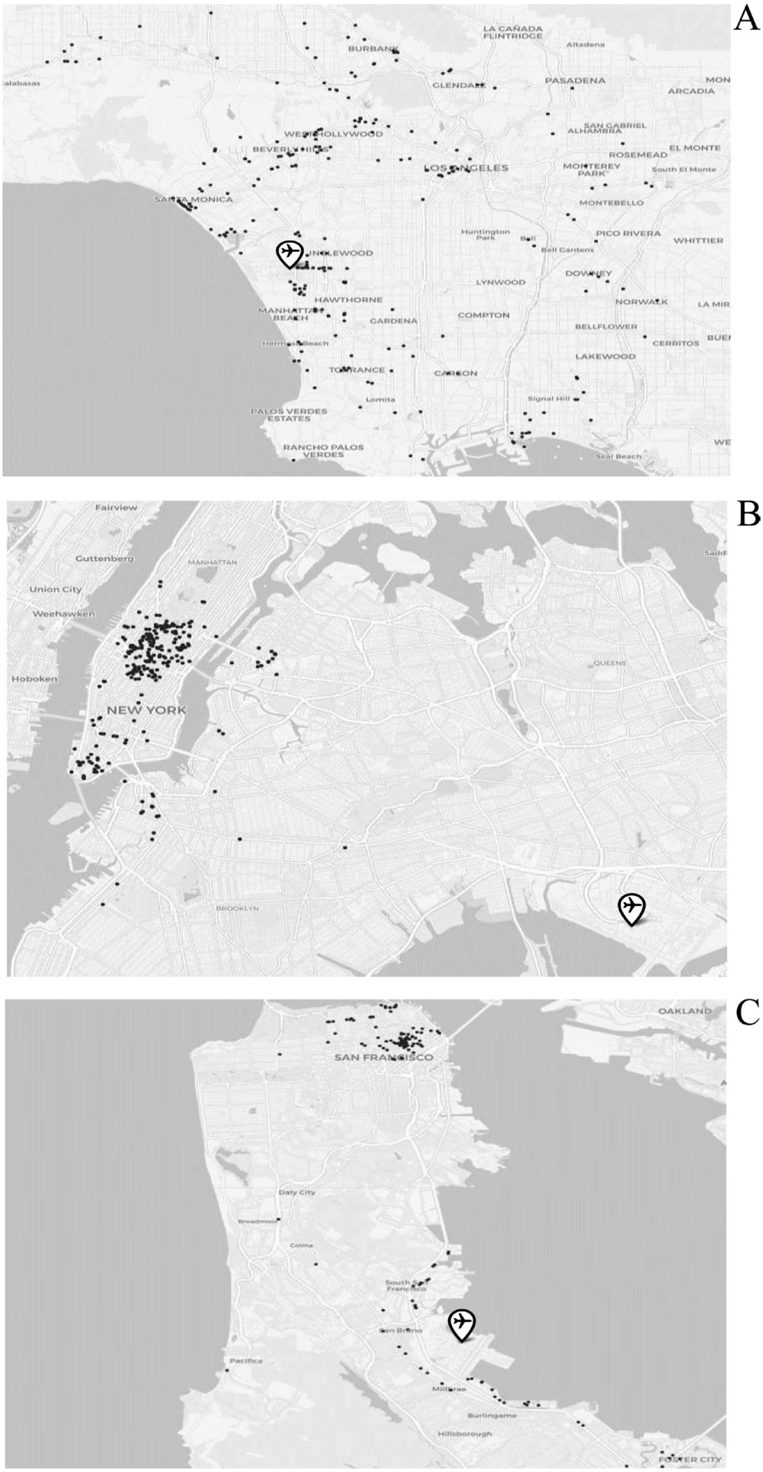

Figure 2. Sample airports and hotel locations. *A,* Los Angeles International Airport; *B,* John F. Kennedy International Airport; *C,* San Francisco International Airport.

Table 1
Summary Statistics: Rides and Hotel Rates by City

	Los Angeles	New York	San Francisco
Ride:			
Fare ($)	31.61	64.56	31.46
	(15.58)	(9.14)	(10.08)
Distance (miles)	15.34	18.56	12.00
	(8.41)	(2.53)	(5.02)
Duration per trip (minutes)	31.62	45.70	21.49
	(14.89)	(12.00)	(10.02)
Duration per mile (minutes)	2.43	2.49	1.86
	(.96)	(.68)	(.47)
Waiting time (minutes)	4.50	3.20	2.58
	(2.32)	(1.24)	(1.40)
N	1,582,694	1,510,151	928,785
Room rate ($)	218.45	336.05	336.15
	(119.80)	(150.85)	(191.16)
N	261	242	152

Note. Values are means, with standard deviations in parentheses.

3.3. *Identification Strategies*

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

$$P_{jt} = \beta \mathrm{HP}_{jt} + \gamma_0 + \gamma_1 \mathrm{Distance}_{jt} + \gamma_2 \mathrm{Duration}_{jt} + \sum_{t=1}^{T} \psi_t \mathrm{Time}_t + \varepsilon_{jt}, \quad (3)$$

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; $\mathrm{Distance}_{jt}$ and $\mathrm{Duration}_{jt}$ are the trip's distance and duration per mile, respectively; Time_t is the group of time fixed effects specified as 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 at the destination, which can 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 UberX 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 specify a linear functional form for the hedonic pricing model. For sensitivity purposes, we also estimate hedonic pricing models that specify the natural log of UberX fares and the natural log of hotel prices, and we obtain 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 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 ho-

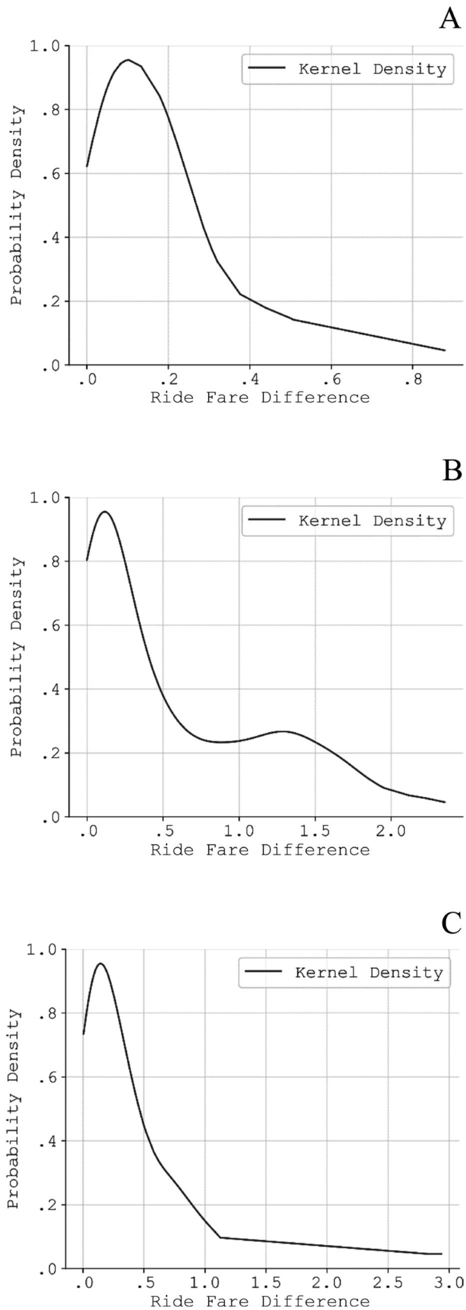

Figure 3. Distribution of fare differences between matched route pairs. *A,* Los Angeles International Airport; *B,* John F. Kennedy International Airport; *C,* San Francisco International Airport.

tels within a .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 UberX trips are made over virtually the same stretch of road.

The effect of the matching assumption, as shown in Figure 4, is to compress the destinations in Los Angeles, New York, and San Francisco and to make them less separated than the destinations in Figure 2. The assumption also reduces the number of routes and the sample sizes because some hotels do not have neighbors within a .1-mile radius.

We specify the geographic matching regression model as

$$P_{jt} = \beta_0 \text{LocHP}_{jt} + \beta_1 \text{DLocHP}_{jt} + \gamma_0 + \gamma_1 \text{Distance}_{jt} + \gamma_2 \text{Duration}_{jt} + \sum_{t=1}^{T} \psi_t \text{Time}_t + \varepsilon_{jt}, \tag{4}$$

where LocHP_{jt} is the mean of the average room rates of the hotels within a .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 .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}. The term LocHP_{jt} measures the average price of neighboring hotels, so a positive value for 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 in a small area, controlling for the heterogeneity in travel conditions and for other possible unobserved influences on the UberX 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 2.35, 4.04, and 3.85 in Los Angeles, New York, and San Francisco, respectively. The average for Los Angeles is lower than that for New York and San Francisco because the density of hotels in Los Angeles is lower. The average room rates of the grouped hotels are not notably different from those of the individual hotels (see Table 1). But grouping does reduce the number of hotels in the sample and the sample size because hotels without close neighbors are no longer included. Finally, Table 2 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 rate of its neighboring hotels is generally small and not statistically significantly different from 0 in all three 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 of the trips from a given airport to a hotel. We report separate estimation results for each city,

Figure 4. Geographically matched hotels. *A,* Los Angeles International Airport; *B,* John F. Kennedy International Airport; *C,* San Francisco International Airport.

Table 2
Summary Statistics: Matched Neighboring Hotels

	Los Angeles	New York	San Francisco
Neighboring hotels in group	2.35	4.04	3.85
	(.67)	(2.20)	(2.38)
Average group room rate (LocHP, \$)	244.88	349.14	338.62
	(86.63)	(121.98)	(103.07)
Hotel *j*'s rate − average rate of neighboring hotels (DLocHP, \$)	.43	−3.75	7.07
	(63.62)	(156.75)	(134.39)
Neighboring hotels (*N*)	55	202	78

Note. Hotel *j* is a neighbor of hotel *k* if it is within a .1-mile radius of hotel *k*. Values are means, with standard deviations in parentheses.

and we specify the average room rate for a hotel on a given route in two 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 UberX because they are positive and statistically significant for all the airports. The estimates for HighHP indicate that a passenger taking an UberX trip to a hotel that has a room rate that exceeds the average room rate would pay, on average, \$1.03, \$.85, and \$.63 more for a trip in Los Angeles, New York, and San Francisco, respectively. The estimates for HP indicate that a passenger would pay \$.54, \$.16, and \$.10 more for a 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, trips' distance and duration have a positive effect on fares, and the coefficients are statistically significant. The effect of a trip's 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.

Table 4 presents the parameter estimates of the matching model given in equation (4), which also provide evidence that Uber engages in price discrimination. The coefficients for the average room rates of grouped hotels and the difference between a hotel's average room rate and that of neighboring hotels are positive and statistically significant in all cities. The estimates indicate that a traveler's fare on UberX would increase by \$.19–\$.90 (.29–2.8 percent) as the average rate of neighboring hotels within .1 mile of each other increases by \$100, and a traveler's fare on UberX would increase by \$.02–\$.05 (.03–.16 percent) for each \$100 difference between the average rate of neighboring hotels and that of the hotel 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 ho-

[12] The price increases correspond to percentage increases of 1.71, .25, and .32 per trip. Given that the percentage changes are calculated as (dollar amount/sample mean of the ride fare) $\times$ 100, where the sample means are \$31.61, \$64.56, and \$31.46 for each city, the percentage increases are greater for shorter routes.

Table 3
Route-Based Fare Discrimination Parameter Estimates

	Los Angeles		New York		San Francisco	
	(1)	(2)	(3)	(4)	(5)	(6)
HighHP	1.0296**		.848**		.6311**	
	(.0141)		(.0086)		(.0122)	
HP		.0054**		.0016**		.001**
		(.0001)		(.0000)		(.0000)
Distance	1.6029**	1.6069**	2.602**	2.6133**	1.8196**	1.8386**
	(.0015)	(.0015)	(.0023)	(.0023)	(.0013)	(.0012)
Duration	1.7806**	1.7888**	7.8456**	7.8553**	2.4870**	2.5079**
	(.0118)	(.0118)	(.0121)	(.0121)	(.0116)	(.0115)
Constant	5.7304**	4.9801**	−4.3292**	−4.6928**	7.0925**	6.8309**
	(.0591)	(.0596)	(.0558)	(.0565)	(.049)	(.0487)
N	1,582,694	1,582,694	1,510,151	1,510,151	928,785	928,785

Note. The dependent variable is P_{jt}. Coefficients of time fixed effects are omitted. Robust standard errors are in parentheses.
** Significant at the 1% level.

Table 4

Route-Based Geographic Matching Fare Discrimination Parameter Estimates

	Los Angeles		New York		San Francisco	
	(1)	(2)	(3)	(4)	(5)	(6)
HighHP	.009**	.0089**	.0019**	.0019**	.0053**	.0053**
	(.0002)	(.0002)	(.0000)	(.0000)	(.0001)	(.0001)
HP		.0005**		.0002**		.0002**
		(.0002)		(.0000)		(.0001)
Distance	1.5724**	1.5724**	2.4585**	2.4585**	1.8471**	1.8471**
	(.0034)	(.0034)	(.0028)	(.0028)	(.0016)	(.0016)
Duration	1.4187**	1.4173**	7.3972	7.3978**	2.4459**	2.4460**
	(.0221)	(.0221)	(.014)	(.014)	(.0172)	(.0172)
Constant	4.6825**	4.6857**	−.752**	−.7684**	5.5206**	5.5187**
	(.1159)	(.116)	(.0689)	(.069)	(.0694)	(.0694)
N	333,522	333,522	1,164,502	1,164,502	476,627	476,627

Note. The dependent variable is P_{jt}. Coefficients of time fixed effects are omitted. Robust standard errors are in parentheses.
** Significant at the 1% level.

tels, which limits the range of the reservation prices of UberX 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.

4.1. Robustness Check: Trips' Distance and Duration

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

4.2. Robustness Check: Supply Shocks

We conduct a robustness check to account for shocks that may affect the supply of drivers at the airport and UberX fares by including a traveler's wait time in the specification, which is closely related to the number of available drivers. The variable Wait Time_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 Wait Time_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 endpoint of each road segment within the city's limits. Figure 5 shows a section of road that provides access to Kennedy Airport. Note that the lane of interest runs in an opposite direction from the hotels in Manhattan, so the average travel time to pass through the section is unrelated to UberX fares. However, the lane is used in part to enter the airport, and the travel time on it affects a passenger's waiting time for UberX. We use the average travel time at time t on the section of road indicated in Figure 5 as an instrument for Wait Time_t, and we estimate the fare regression model for New York with a two-stage least squares (2SLS) model. (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' waiting times 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 in-

Figure 5. Traffic sensors on a John F. Kennedy International Airport route

strument waiting times. The positive OLS and 2SLS coefficients of Wait Time$_t$, which are statistically significant, indicate that reductions in the supply of drivers that increase waiting times increase UberX fares, although the effect is much larger when we account for the endogeneity of waiting times.

4.3. Robustness Check: Frequency of UberX Observations

We collect data for UberX every 20 minutes to account for the variation in UberX fares and operations throughout the day and on different days. The high-frequency data also generate 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 are not based on actual trips. In practice, trips departing from an airport could occur less frequently, especially outside peak travel periods during the day and possibly on certain days of the week. We therefore explore whether the findings might be affected if we use a sample based on an hourly frequency of UberX observations.

Table A1 reports estimation results using observations obtained hourly, which we construct from averages of the 20-minute frequency observations in hourly blocks. We present parameter estimates for alternative specifications of the UberX fare, which we 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 UberX for a greater frequency of trips—every 10 minutes—but Uber's API would not allow us to do so.

Table 5

Route-Based Fare Discrimination Parameter Estimates for New York

	Ordinary Least Squares			Two-Stage Least Squares		
	(1)	(2)	(3)	(4)	(5)	(6)
HighHP	.8491**			.8468**		
	(.0087)			(.009)		
HP		.0016**			.0016**	
		(.0000)			(.0000)	
LocHP			.0019**			.0019**
			(.0000)			(.0000)
DLocHP			.0002**			.0002**
			(.0000)			(.0000)
Distance	2.5995**	2.6107**	2.4557**	2.6046**	2.6158**	2.4614**
	(.0023)	(.0023)	(.0029)	(.0025)	(.0025)	(.0031)
Duration	7.8344**	7.8440**	7.3903**	7.8606**	7.8701**	7.4212**
	(.0122)	(.0122)	(.0141)	(.0129)	(.0129)	(.015)
Wait Time	.2269**	.2272**	.2238**	1.6660**	1.6661**	1.7092**
	(.0055)	(.0055)	(.0061)	(.2532)	(.2534)	(.2862)
Constant	−4.9348**	−5.3000**	−1.3681**	−9.7133**	−10.077**	−6.3195**
	(.0597)	(.0604)	(.0731)	(.8416)	(.8424)	(.9546)
N	1,482,233	1,482,233	1,143,168	1,482,233	1,482,233	1,143,168

Note. The dependent variable is P_{jt}. Coefficients of time fixed effects are omitted. Robust standard errors are in parentheses.
** Significant at the 1% level.

4.4. Robustness Check: Weighting Observations Sampled at Different Times of Day

Market competition faced by Uber varies by time of day. For example, public transportation is largely unavailable after midnight, which enables Uber's pricing power to increase and raises concerns that our findings could be sensitive to the temporal distribution of the trip data. Because we have vehicle trip data between Kennedy Airport and taxi zones of New York City, including Uber trips, we conduct a robustness check by estimating a weighted regression in which observations at different times of day are weighted by the share of Uber trips in all vehicle trips. The estimation results presented in 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 UberX 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 on the basis of 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 particular 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 ride-sharing services and by comparing travelers' welfare under discriminatory pricing with that under a uniform price imposed to prohibit price discrimination.

The hedonic regressions estimated above are 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 those data does not allow us to determine the total demand for ride-sharing services, which we need to estimate the demand for all ride-sharing services. As an alternative data source, we use comprehensive trip records in New York City that are collected by the New York City Taxi and Limousine Commission to estimate the demand for ride-sharing services. The data include services provided by Uber and Lyft, so the rideshare product types that we include are Uber, UberPool, Lyft, and Lyft Shared.

The trip records are measured in New York City taxi zones, which are roughly aligned with neighborhood planning areas. We estimate a ride-sharing demand model by constructing a panel data set 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 in 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

$$\begin{aligned}\text{Log}(Q_{ikt}) = \phi_0 + \phi_1 \text{Log}(P_{ikt}) + \phi_2 \text{Log}(P_{ikt})\overline{\text{HP}}_k + \sum_{i=1}^{I} \omega_i \text{Type}_i \\ + \sum_{t=1}^{T} \psi_t \text{Time}_t + \sum_{k=1}^{K} \mu_k \text{Zone}_k + \varepsilon_{ikt},\end{aligned} \tag{5}$$

where Q_{ikt} is the number of trips of rideshare 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; $\overline{\text{HP}}_k$ is the average hotel price in zone k; Type_i, Time_t, and Zone_k are the rideshare 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 $\overline{\text{HP}}_k$ in the demand function to estimate a heterogeneous price elasticity that varies by 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—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 predetermined by the traveler arriving at the airport. Rideshare companies' profit-maximizing pricing decisions are influenced by those time-varying cost differences across taxi zones and times, but random shocks, such as traffic accidents, affecting the demand for ride-sharing 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

[13] The fare data are the same fare data that we use above. Thus, we again assume that the rideshare product types by 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 rideshare 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.

[15] Shocks to congestion are exogenous because fluctuations in demand for rideshare services are unlikely to affect congestion in a particular zone conditional on time fixed effects. However, real-time pricing algorithms of rideshare 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 ride sharing, which would affect demand. We assume that such congestion delays rarely occur.

Table 6
First-Stage Estimates of Rideshare Demand

	20-Minute Frequency		60-Minute Frequency	
	$\text{Log}(P_{ikt})$	$\text{Log}(P_{ikt})\overline{\text{HP}}_k$	$\text{Log}(P_{ikt})$	$\text{Log}(P_{ikt})\overline{\text{HP}}_k$
Distance	.0251**	8.7748**	.0253**	8.7688**
	(.0001)	(.0776)	(.0002)	(.0934)
Duration	.0151**	5.7574**	.0157**	6.0481**
	(.0005)	(.2139)	(.0006)	(.2624)
Speed	−.0011**	−.301**	−.0008**	−.1832**
	(.0001)	(.0363)	(.0001)	(.042)
Constant	3.6175**	1,130.235**	3.6055**	1,128.17**
	(.0059)	(2.4505)	(.007)	(2.9386)
R^2	.8662	.9944	.8825	.9943
N	122,907	122,907	88,185	88,185

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

in Table 6, indicate that all the instruments have a statistically significant effect on price, and the high R^2-values suggest that the instruments are not weak.[16] As a robustness check, we use 60 minutes instead of 20 minutes as our unit of time by grouping data from various 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. Results for 20-minute frequencies indicate that travelers' demand for ride-sharing services is inversely related to price, while travelers' sensitivities to price decrease as average hotel prices increase, which indicates that they have heterogeneous preferences that ride-sharing companies cater to with price discrimination. Estimates for 60-minute frequencies show that the results are not sensitive to using a longer unit of time to generate the observations. Using the 2SLS coefficients, we calculate that the price elasticity of demand (at the mean of $\overline{\text{HP}}_k$) is −.065 and −.152 for 20- and 60-minute frequencies, respectively, although the difference is not statistically significant. The inelastic demand elasticity estimates are plausible 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 60-minute 2SLS equation in Table 7.[17] We predict the discriminatory prices by using the observed hotel room rates and the average room rate as specified in the

[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.

[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.

Table 7
Rideshare-Demand Parameter Estimates

	20-Minute Frequency		60-Minute Frequency	
	Ordinary Least Squares	Two-Stage Least Squares	Ordinary Least Squares	Two-Stage Least Squares
Log(P_{ikt})	−.0525**	−4.7257**	−.1806**	−4.7044**
	(.0201)	(1.2379)	(.0304)	(1.4215)
Log(P_{ikt})$\overline{\mathrm{HP}}_k$	.0002**	.0138**	.0006**	.0136**
	(.0000)	(.0036)	(.0001)	(.0041)
Constant	−.16133**	−16.8702**	−.2023**	8.6951**
	(.0461)	(4.2273)	(.0709)	(2.8268)
N	125,046	122,907	89,698	88,185

Note. The dependent variable is log(Q_{ikt}). Coefficients of product type, time, and zone fixed effects are not shown. Robust standard errors are in parentheses.
** Significant at the 1% level.

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

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

where P_{Unif} is the uniform price, P_{Disc} is the discriminatory price, and $f(P) = P^{\hat{\phi}_1 + \hat{\phi}_2 \overline{\mathrm{HP}}_k}$ 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 \$.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 the destination. The aggregate change in consumer surplus therefore could be small because those effects offset each other.

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, ride-sharing companies are willing to offer lower fares as a reward to increase traffic and the use of drivers' vehicles on less popular routes.

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

Table 8

Consumer Welfare Impacts of Price Discrimination

	20-Minute Frequency	60-Minute Frequency
Proportion of $+\Delta$CS	74.5	75.4
ΔCS ($)	+.0088	+.0071
	(.0001)	(.0001)

Note. Values are differences in consumer surplus between price discrimination and uniform pricing. Plus signs indicates that consumer surplus increases when price discrimination is adopted. Standard errors, in parentheses, are calculated with the bootstrap method using the estimated coefficients and random sampling from the trip record data (with replacement).

6. Conclusions

Price discrimination by firms may enhance consumer welfare by giving consumers greater opportunities to purchase goods and services 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 used price data for hypothetical trips provided by Uber, which align closely with the prices that travelers would have paid if they had taken those trips, to test for the existence of price discrimination in three markets defined by the same airport origin and different hotel destinations. We obtained robust findings that travelers staying at more expensive hotels pay higher fares, all else equal, than travelers staying at less expensive hotels. Importantly, we also found that discriminatory fares improve travelers' welfare compared with a uniform fare mandated by a regulatory authority to prohibit price discrimination. We suggest that discriminatory fares in rideshare markets benefit rideshare companies and travelers by expanding travel options for travelers and by increasing the 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.

Appendix

Additional Tables

Table A1

Route-Based Fare Discrimination Parameter Estimates: Hourly Observations

	Los Angeles			New York			San Francisco		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HighHP	1.0258**			.7932**			.6257**		
	(.0182)			(.0125)			(.016)		
HP		.0054**			.0015**			.0009**	
		(.0001)			(.0000)			(.0000)	
LocHP			.0088**			.0018**			.0052**
			(.0002)			(.0001)			(.0001)
DLocHP			.0005+			.0002**			.0002**
			(.0003)			(.0000)			(.0001)
Distance	1.6009**	1.6050**	1.5723**	2.7233**	2.7362**	2.585**	1.8202**	1.8392**	1.8479**
	(.002)	(.002)	(.0045)	(.0035)	(.0036)	(.0044)	(.0018)	(.0016)	(.0021)
Duration	1.7274**	1.7360**	1.3609**	8.2341**	8.2417**	7.8214**	2.4582**	2.4796**	2.3712**
	(.0164)	(.0163)	(.0312)	(.0186)	(.0187)	(.0214)	(.0163)	(.0162)	(.0243)
Constant	5.8218**	5.0681**	4.8102**	−7.1948**	−7.5628**	−3.7957**	7.0825**	6.8208**	5.5871**
	(.0752)	(.0757)	(.1512)	(.0838)	(.0851)	(.105)	(.0654)	(.0649)	(.0922)
N	537,382	537,382	113,238	509,509	509,509	392,774	316,004	316,004	162,160

Note. The dependent variable is P_{jt}. Coefficients of time fixed effects are omitted. Robust standard errors are in parentheses.
+ Significant at the 10% level.
** Significant at the 1% level.

Table A2

Weighted-Regression Estimates of Route-Based Price Discrimination Parameters for New York

	(1)	(2)	(3)
HighHP	.7544**		
	(.01)		
HP		.0012**	
		(.0000)	
LocHP			.0011**
			(.0001)
DLocHP			.0001**
			(.0000)
Distance	2.6153**	2.6265**	2.4788**
	(.0026)	(.0026)	(.0032)
Duration	7.3624**	7.3789**	6.8401**
	(.0134)	(.0135)	(.0158)
Constant	−3.8073**	−4.0929**	−.052**
	(.0615)	(.0623)	(.078)
N	1,582,694	1,510,151	928,785

Note. The dependent variable is P_{jt}. Coefficients of time fixed effects are omitted. Robust standard errors are in parentheses.
** Significant at the 1% level.

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