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# LEAVING MONEY ON THE DASHBOARD: PRICE DISPERSION AND SEARCH FRICTIONS ON UBER AND LYFT

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**ABSTRACT**

We document price differences for identical trips on Uber and Lyft, based on an audit of the two platforms. While price dispersion exists in the market, device-level data show that only 16.1 percent of consumers opening one app also open the other. Our estimates suggest that the modest frictions involved in comparison shopping increase platforms' gross booking volume by over $300 million annually in New York City alone. While price-comparison engines could in principle reduce frictions, Uber's API terms of use limit such services, reducing riders' ability to price compare.

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# 1 Introduction

Competition can only discipline prices when consumers actively compare across firms. Ridesharing services in the US provide a compelling setting to study this process: a market with two dominant platforms, Uber and Lyft, in which price comparison requires little more than opening a second app.

Using a synchronized audit of Uber and Lyft, we document substantial price differences for identical trips in New York City. Instead, device-level usage data show that, conditional on opening one app, only 16.1 percent of the time consumers also open the other on the same day.

Optimal search decisions depend on the distribution of price gaps and the magnitude of search costs. To explore, we calibrate a simple sequential search model. The model predicts over 90 percent comparison–far higher than the observed frequency. This helps to explain why price dispersion persists in a duopoly market in which search is straightforward. Our approach combines a synchronized field audit with device-level behavioral data, a design that can be adapted to study consumer search and competition in other digital markets.

Our analysis contributes to the literature linking consumer search costs, price dispersion, and market efficiency (Stigler (1961), Diamond (1971), Burdett and Judd (1983), Stahl (1989), Salop and Stiglitz (1982), Rob (1985)), as well as literature exploring the ways in which information and search frictions can materially shape market outcomes (e.g. Argente et al. (2025), Bergemann and Bonatti (2019)).

Our work also connects to the literature on search costs in the digital age. Early work highlighted the potential of the Internet to dramatically reduce search costs and improve market efficiency (Bakos (1997), Brynjolfsson and Smith (2000)). While there have been reductions in prices (Brynjolfsson and Smith (2000), Scott-Morton et al. (2001), Brown and Goolsbee (2002)), persistent dispersion in online markets remains (Brynjolfsson and Smith (2000), Baye et al. (2004), Baye et al. (2006)) and has led researchers to highlight the potential role of obfuscation (Ellison and Ellison (2009), Ellison and Wolitzky (2012), Blake et al. (2021)) and behavioral frictions (Baye et al. (2006)) as explanations.

Ridesharing services in the US provide a useful case study for exploring these topics. In 2023 Lyft reported \$13.8 billion in bookings on 709 million rides, while Uber reported \$138 billion on 9.4 billion trips (Lyft, Inc. (2023), Uber Technologies, Inc. (2024)). Competition is concentrated between two major firms offering a largely homogeneous service, enabling us to observe prices for comparable services. Conditional on having both apps installed, price comparison is technologically simple: open a second app, enter a location, and view a quote. This suggests that search costs should, in principle, be low. Finally, ridesharing is accessed almost exclusively through mobile devices, making it a natural environment to study how mobile interfaces shape consumer search. Prior work suggests that search costs may be higher on mobile relative to desktop settings due to smaller screen sizes (Ghose et al. (2013)).

There are several main limitations of our analysis. First, our panel of price audits is different from our panel of app usage. Second, in our app usage data, we observe decisions about which apps are opened, but not final bookings. Third, our analysis is on base price, and abstracts from potential personalized discounts. Nonetheless, the evidence consistently points to low rates of search, despite persistent dispersion.

Taken together, our results suggest that consumers compare prices substantially less often than canonical models predict, even under generous assumptions about search costs–though this could also be consistent with other nuisance costs. Our findings shed light on the extent of consumer search and the relevance of behavioral frictions, and provide a starting point for understanding competition in ridesharing markets. They also raise questions of policy relevance: because these frictions lead to too little search, they harm consumer welfare and limit competition.

The paper proceeds as follows. First, in Section 2.2, we document the extent of price dispersion in the rideshare market across a representative sample of trips in New York City. Across trips, we find that the average absolute price gap between Uber and Lyft is approximately \$3.50, or about 14% of the average fare price, suggesting that consumers stand to gain from comparing prices. Second, in Section 2.3, we document the extent of consumer search using device-level data, finding that price comparison is relatively uncommon despite potential benefits: conditional on opening at least one rideshare application on a given day, only 16.1% of devices open both applications. Next, in Sections 3 and 4, we introduce and calibrate a simple sequential search model to benchmark observed search behavior against theoretical predictions. Across these exercises, we find that consumers compare prices less than canonical search models would predict under benchmark assumptions about the cost of consumer search. Finally, in Section 5, we conduct a simple back-of-the-envelope calculation to estimate the aggregate welfare effects, finding that New York City-based rideshare customers collectively leave over \$300 million on the table due to a lack of price comparison.

# 2 Empirical Setting and Data

## 2.1 Empirical Setting

The setting for this paper is the consumer rideshare market. As discussed in Section 1, this is a substantial consumer market dominated by two major firms in the United States: Uber and Lyft. Most consumers access the market via mobile devices. Prices in this market are presented to consumers up-front before a ride is requested. See Figure A1 for an example of this information in the two mobile apps. Importantly, "prices" in this market have two components: (1) the raw dollar price of the ride, and (2) the "wait time" of the ride – i.e. how long the consumer will need to wait before being picked up; we discuss these two dimensions of prices further in Section 2.2.4 below.

## 2.2 Price Dispersion in the Rideshare Market

### 2.2.1 Price Audit Data Collection

To understand the extent of price dispersion in the rideshare market, we conduct an audit of prices on Uber and Lyft for a representative sample of trips in New York City over the course of one week between February 13th, 2025 and February 19th, 2025. We focus on New York City due to the availability of public data from the New York City Taxi & Limousine Commission (hereafter NYC TLC) which documents all rideshare trips taken in the city [1]. We use this data to audit prices for a sample of trips which matches the temporal and geographical distribution of Uber and Lyft trips taken in the city in a particular week, allowing us to understand the extent of price dispersion faced by a typical rideshare customer in New York City. Our data preparation process proceeds as follows.

First, we create a "reference" sample of Uber and Lyft trips from the February 2024 NYC TLC trip data. To do this, we randomly sample rideshare trips from a reference week in 2024 (February 15, 2024 to February 21, 2024) which matches the week of our audit; sampling is stratified at the hour-of-week level to maximize the amount of data we are able to collect. We additionally enforce a constraint that no two reference trips are within 2 minutes of one another to avoid interference between observations in the data collection phase. For the sample of reference trips, we observe a range of metadata including the trip's date and time, length in miles, and its origin and destination at the "taxi zone" level[2].

[1] See `https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page`

[2] New York City is divided into 263 non-overlapping taxi zones which roughly correspond to city neighborhoods (e.g. "East Village, Manhattan", "Forest Hills, Queens" etc.). The precise names and geographical extent of these zones is available on the NYC TLC website: `https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page`

Second, we convert our reference trips into origin and destination addresses that can be searched on the Uber and Lyft platforms. To do this, we rejection sample random latitude-longitude pairs within the origin and destination taxi zones indicated in the NYC TLC data, reverse geo-code these points to address strings, and then compute the street distance between them using Google until we find an origin-destination address pair that matches the reference trip distance within a tolerance of 0.5 miles. Matching on trip distance is especially important for trips that start and end in the same or adjacent taxi zones, to ensure that we do not over-sample very short trips.

Third, we construct automated tooling to collect price quotes from the Uber and Lyft platforms for the audit trip at the same minute of the week (e.g. Thursday at 2:53pm) as the reference trip. All price quotes are collected using a single Android device on new Uber and Lyft accounts without any previous ride history and identical rider details. On both platforms, we search for the address generated in the data preparation process, select the first match offered by the platform, and then store price and wait time information quoted by the platform for the trip. We collect price quotes from Uber and Lyft in a randomized order to ensure we do not introduce any bias from consistently checking one app first.

While we search on both Uber and Lyft using identical origin and destination address strings, the two platforms sometimes interpret these addresses as different locations (e.g. if an address name is present in multiple NYC boroughs). This presents a concern for our analysis since if our audit trips are not matched across the platforms, it could lead us to overstate the extent of price dispersion. Hence, after collecting the audit data, we undertake an extended data cleaning process that combines string matching, LLM inspection, and manual validation to ensure that our results are not biased by mismatched trips. We additionally exclude a number of cases where the automated tooling fails to successfully collect a price quote for one or both platforms. See Figure A4 for a complete outline of this process. Manual validation on a random sample of 100 trips estimates that at least 98% of the trips that remain in our audit sample are accurately matched across platforms. The final audit sample includes 2,238 matched price quote observations. Note that while the rideshare platforms offer a variety of travel options (e.g. shared rides, "XL", and "Green" options; see Figure A1), we will focus specifically on the baseline "UberX" and "Lyft (Standard)" offerings which are comparable across the two platforms.

### 2.2.2 Prices and Price Dispersion on Uber and Lyft

In this section, we present summary statistics about prices and price dispersion on Uber and Lyft based our audit sample. Let $\text{Price}_{ij}$ and $\text{Wait}_{ij}$ be the quoted price and wait time (in minutes) for platform $i \in \{\text{Uber}, \text{Lyft}\}$ for trip $j$. Per above, note that a trip $j$ is defined by an origin, destination, and time of the week (e.g. 1051 Riverside Dr, New York, NY to 1341 Purdy St, Bronx, NY on Thursday at 12:37 AM). Next, define the "price gap" as the price difference between Uber and Lyft for a focal trip and define the "wait gap" analogously:

$$\text{PriceGap}_j = \text{Price}_{\text{Uber},j} - \text{Price}_{\text{Lyft},j}.$$

The measure $\text{PriceGap}_j$ and its absolute value $|\text{PriceGap}_j|$ provide a simple approach to understand the extent of price dispersion in this market. Intuitively, if the typical value of $|\text{PriceGap}_j|$ is large relative to search costs, and the distribution of $\text{PriceGap}_j$ is relatively symmetric about zero, then consumers stand to benefit from comparing prices between the two platforms.

Figure 1 displays the distribution of price gaps, weighted to account for our stratified sampling scheme described above. Weighting is implemented at the hour-of-week level based on the distribution of trips in our reference week from the NYC TLC trip data; these weights are displayed in Figure A5 and an unweighted version is provided as Figure A7.

The figure shows two important facts. First, we find that there is persistent price dispersion between platforms in this market. Per Panel B, $|\text{PriceGap}_j|$ exceeds \$1 approximately 75% of the time [3]. Second, the distribution of price gaps is relatively symmetric about zero, meaning that neither rideshare app is consistently more expensive than the other. Together, these facts suggest potential gains for consumers from comparing prices.

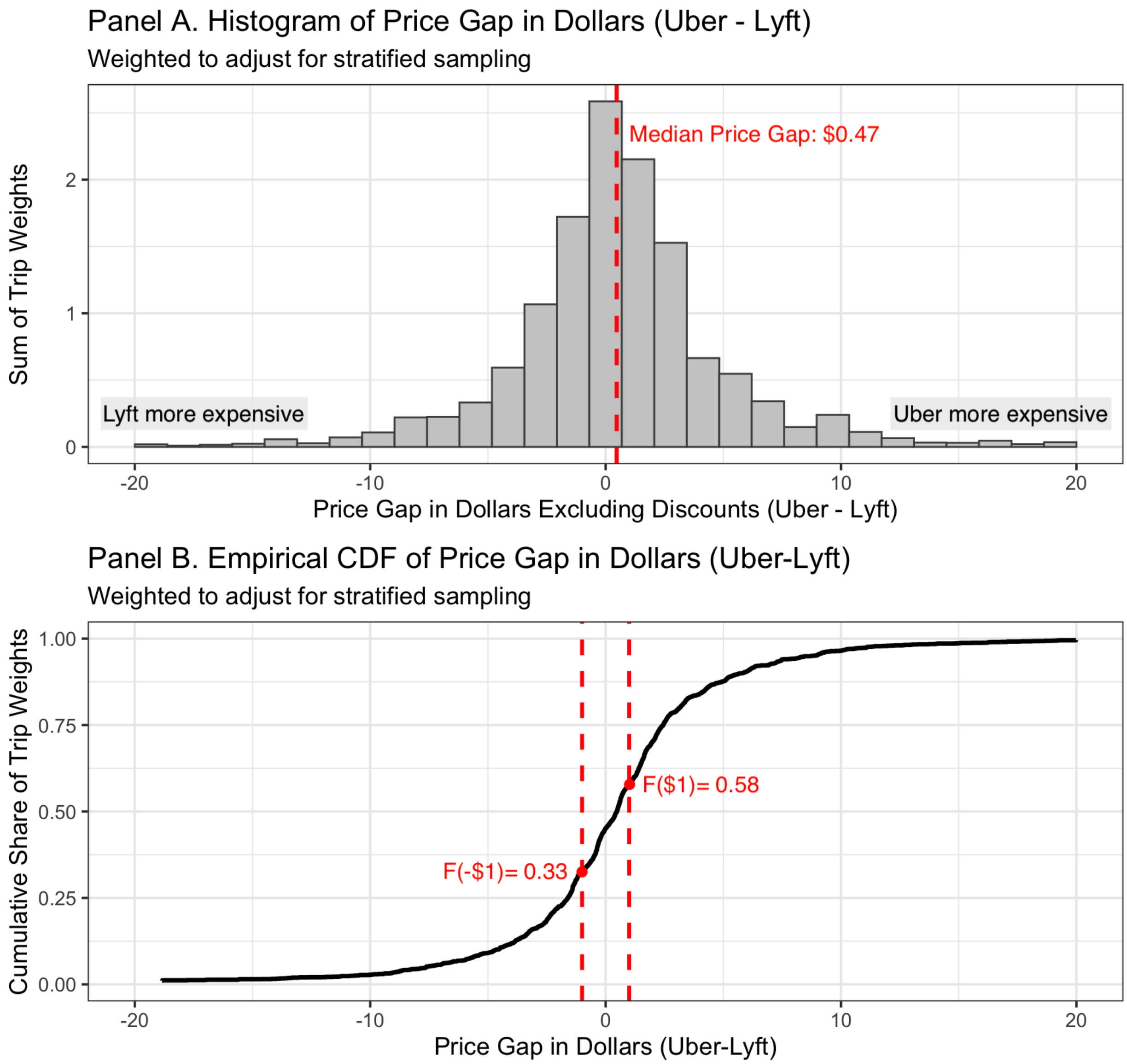
These points are further explored in Table 1, which presents summary statistics of prices and price gaps both overall and broken down by weighted quintiles of trip length. Overall, the table shows that a similar pattern of price gaps persists across trips of different lengths, with column (4) showing that the average absolute price gap grows for longer–and hence more expensive–trips. Column (5) normalizes column (4) by the overall average fare price in the trip segment; this column shows that the average absolute price gap is consistently about 12-15% of the mean fare price, even as fare price increases for longer trips. Assuming consumer search costs are constant across different trip distances, Table 1 suggests that consumers stand to benefit more from comparing prices for longer, more expensive, trips.

#### 2.2.3 Personalized Pricing on Uber

Our analysis focuses on base prices, abstracting from personalized promotions or discounts that particular riders may receive. From conversations with industry experts, our understanding is that both Uber and Lyft offer a variety of targeted personalized promotional discounts to riders which can depend on app usage or other rider characteristics. Anecdo-

[3] $F(-\$1) + (1 - F(\$1)) = 0.33 + 0.42 = 0.75$

Figure 1: Price Dispersion Between Uber and Lyft for Identical Trips




*Notes: This figure shows the distribution of* $PriceGap_j = Price_{Uber,j} - Price_{Lyft,j}$ *as defined in section 2.2.2 excluding promotions and discounts. Panel A is a weighted histogram. Panel B is a weighted empirical CDF. In both cases, weights adjust for the stratified random sampling scheme also described in section 2.2.2.*

Table 1: Prices & Price Dispersion by Trip Length

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **Trip Distance Quintile** | **Uber Price ($)** | **Lyft Price ($)** | **Price Gap ($)** | **Abs. Price Gap ($)** | **Normalized Abs. Price Gap (%)** |
| Q1 (0.17–1.24 mi) | 12.19<br>(0.25) | 11.91<br>(0.25) | 0.28<br>(0.14) | 1.83<br>(0.10) | 15.22<br>(0.81) |
| Q2 (1.24–1.99 mi) | 16.30<br>(0.29) | 16.90<br>(0.29) | -0.60<br>(0.15) | 2.04<br>(0.11) | 12.27<br>(0.62) |
| Q3 (1.99–3.09 mi) | 21.50<br>(0.35) | 20.40<br>(0.33) | 1.10<br>(0.20) | 2.77<br>(0.15) | 13.24<br>(0.64) |
| Q4 (3.09–5.62 mi) | 28.88<br>(0.44) | 27.59<br>(0.49) | 1.29<br>(0.31) | 4.25<br>(0.21) | 15.04<br>(0.63) |
| Q5 (5.62–32.92 mi) | 44.97<br>(0.75) | 45.48<br>(0.89) | -0.51<br>(0.51) | 6.74<br>(0.39) | 14.90<br>(0.79) |
| **Overall** | **24.76**<br>**(0.32)** | **24.45**<br>**(0.34)** | **0.31**<br>**(0.13)** | **3.53**<br>**(0.10)** | **14.30**<br>**(0.35)** |

*Notes: Columns (1)-(4) in this table show weighted means and standard errors based on the price audit sample described in section 2.2, both overall and broken out by quintiles of trip length. Weights adjust for the stratified random sampling scheme also described in section 2.2.2. Column (5) is a percentage, computed by dividing column (4) by the mean of columns (1) and (2). Standard errors are computed using 1000 bootstrap replications. All prices exclude promotions and discounts (see Section 2.2.3).*

tally, we have seen rides for which discounts are offered on Lyft but not Uber, and on Uber but not Lyft. In our audit, for example, the account triggered a series of promotional price discounts on the Uber platform but not on Lyft; see Figure A2. We have at other times seen the opposite; see Figure A3 for an example from one of our personal accounts.

As Figures A8 and A9 show, for the new account we set up, discounts on Uber were present throughout data collection, with rates lower and more varied for the first two days, but then jumping to a consistent $\sim 30\%$ for all trips from February 15th onward. In aggregate, 90% of Uber trips in our sample had some form of discount, suggesting that something about the new account – which was set up for the audit – triggered Uber to offer a promotion. For instance, it could be that this new account had never completed a ride, but was consistently checking prices. In this case, Uber may have predicted that the rider's behavior would be impacted by a discount. We did not observe any discounts or promotions in our Lyft data, suggesting that the account set up did not trigger their discount system.

Since we only have data from a single account, a complete analysis of personalized discounts is beyond the scope of this paper. However, this is an important area for future research, as discounts can be significant and little is known about their frequency and usage.

### 2.2.4 Prices and Wait Times

As discussed above, prices in the rideshare market include both fare prices as well as wait time quotes (i.e. how long the platform claims you will need to wait before being picked up by a driver). As shown in Figure A1, we observe both prices and wait time quotes in our audit sample; however, our primary analyses focus only on fare price.

For the purposes of our analysis, one possible concern about this focus on fare prices is that we might *overstate* the effective level of price dispersion (and hence the expected level of price comparison) if differences in fare price are frequently offset by countervailing differences in wait time. In other words, it is possible that price dispersion might be explained by differences in product quality (wait time).

However, in our audit sample, this is not the case. Figure A6 shows a scatter plot of $\text{WaitGap}_j$ against $\text{PriceGap}_j$, with weighted regression line overlaid. The plot shows that, in our sample, the two quantities are actually modestly *positively* correlated, meaning larger price differences are associated with larger wait time differences. Hence, if anything, our focus on price gaps *understates* the wait-time-adjusted level of price dispersion faced by consumers, cutting against our central finding that price comparison rates are low relative to theoretical expectations.

## 2.3 Price Comparison Rate

Having documented the presence of price dispersion in the rideshare market, we now turn to the question of whether consumers compare prices. To investigate, we use a sample of behavioral data from the Comscore mobile data feed. The data include session-level browsing information for a panel of mobile devices tracked by Comscore from September 1, 2023 through November 30, 2023. The data allow us to observe that a particular mobile device opened a given mobile application at a particular date and time; however, we do not observe exactly what actions a user took on a given application, what prices they observed, or whether they requested a ride. We also observe various self-reported demographic characteristics about a subset of Comscore panelists, including their household income bracket, race, gender, age, region, and device type.

To estimate the rate of price comparison rate using this data, we construct a device-day-level panel dataset including all devices that open a rideshare application at least once during the period that the data covers. We exclude devices for which we do not observe any demographic information. The final panel includes 4,016 devices observed across 91 days.

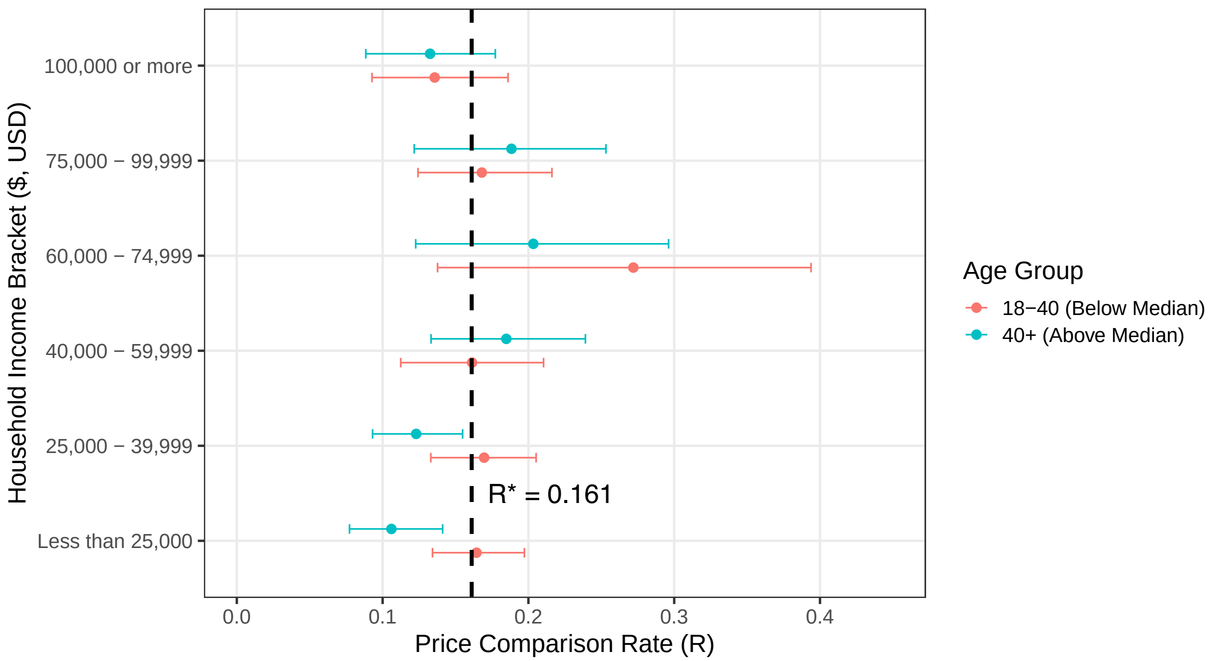
We define a measure of the price comparison rate in the following manner. Let $\text{Uber}_{it} \in \{0, 1\}$ be an indicator for whether device $i$ opened the Uber app at least once on day $t$. Define $\text{Lyft}_{it}$ similarly. Then, define the overall device-day-level price comparison rate as:

$$\text{Price Comparison Rate} = \frac{\sum_{i,t}(\text{Uber}_{it} \cdot \text{Lyft}_{it})}{\sum_{i,t} \max\{\text{Uber}_{it}, \text{Lyft}_{it}\}}.$$

Intuitively, this measure answers the question: given that a device opened any rideshare app on a given day (i.e. Uber or Lyft), what proportion of the time did the device open *both* rideshare apps on that day? We note it is possible that this device-day-level measure of price comparison somewhat *overstates* the true level of purchase-time price comparison e.g. if an individual takes multiple rideshare trips within a single day and uses different applications (without searching) for each trip. Hence, the true level of price comparison may be even lower than what we present.

Figure 2 shows a summary of the price comparison rate in our sample. Note that the overall device-day level rate of price comparison in the sample is 0.161 (or 16.1%), with a 95% confidence interval of $(0.147, 0.177)$. This confidence interval is based on a device-level bootstrap with 1000 bootstrap samples; this approach handles the fact that day-level observations for the same device are not independent. Overall, Figure 2 shows that the rate of consumer price comparison is relatively limited across consumer segments. Additionally, we do not observe systematic patterns by household income or age bracket.

Figure 2: Price Comparison Rate by Household Income Bracket and Age Group




*Notes: This figure shows the device-day-level price comparison rate for the panel of devices defined in the text (see section 2.3 of the text), split by age group (above/below the median age in the sample) and reported household income. The plot shows both point estimates and 95% confidence intervals based on the quantiles of a device-level bootstrap within each subgroup with 1000 bootstrap samples as described in the text. The vertical line shows the overall price comparison rate in the sample.*

# 3 Theoretical Model

## 3.1 Background

To attempt to reconcile the price dispersion observed in Section 2.2 with the relatively low rate of price comparison observed in Section 2.3, we develop and benchmark a simple theoretical model of search for rideshare consumers. The model is based on the optimal sequential search models described in McCall (1970) and Kohn and Shavell (1974). Importantly, the model we present is *not* an equilibrium search model (e.g. in the spirit of Diamond (1971), Stahl (1989), Salop and Stiglitz (1982)) and takes prices as exogenous. Because of this, the model does not speak directly to the effect of consumer search choices on price levels or welfare. However, the simple model will allow us to address the following question: how much search would we expect to see if consumers are searching optimally (under a sequential paradigm), *given* an assumed level of (i) consumer search costs, and (ii) price dispersion. In Section 4 we will present calibration results based on our model for a range of search cost assumptions, and compare these results to the observed level of price comparison presented in Section 2.3.

## 3.2 Model Setup

A representative consumer plans to purchase a homogeneous product (e.g., a rideshare trip) from one of two platforms. Let $K$ be the consumer's intrinsic value for the product. Let $p_i$ be the price of the product on platform $i$, and the prices on the two platforms jointly follow a bivariate normal distribution:

$$\begin{pmatrix} p_1 \\ p_2 \end{pmatrix} \sim \mathcal{N}\left(\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \mathbf{\Sigma} = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}\right)$$

The consumer knows the price distribution but not the actual prices offered by the platforms, and thus needs to search in order to make a purchase decision. The consumer can search one platform at a time; searching for the price on either platform incurs a cost $c$, which can be further decomposed as

$$c = vt,$$

where $v$ is the consumer's opportunity cost (or value) of time in hours, and $t$ is the time in hours it takes to search on either platform[4].

Consumer searches on platform 1 first with probability $\delta$. Suppose that the consumer's

[4] Note that we assume $t$ is the same for both platforms.

intrinsic value for the trip $K$ is sufficiently large, or

$$K > \max\{\mu_1, \mu_2\} + c,$$

such that the consumer always initiates the first search. After each search, the consumer may either continue searching on the other platform (if she has not done it yet), or stop searching and choose among the available options.

## 3.3 Reserve Price and Price Comparison Rate

We start with the scenario where the consumer searches on platform 1 first and observes the price $p_1$, and show that there exists a reserve price $p_1^*$ such that the consumer will price compare, i.e., continue searching on platform 2, if and only if $p_1 > p_1^*$.

If the consumer stops searching right away, she pays $p_1$ for the trip. If she continues searching, she incurs an extra search cost of $c$, but pays the lower of $p_1$ and $p_2$, conditional on the observed price $p_1$. Therefore, the consumer continues searching if and only if the expected extra saving in the price to be paid exceeds the search cost, or

$$p_1 - \mathbb{E}\left[\min\left\{p_1, p_2\right\}|p_1\right] > c \Leftrightarrow p_1 - p_1 \Pr\left(p_2 > p_1|p_1\right) - \mathbb{E}_{p_2|p_1}\left[p_2|p_2 < p_1\right]\Pr\left(p_2 < p_1|p_1\right) > c.$$

Denote

$$\widetilde{p}_1 = \frac{p_1 - \mu_2 - \rho\frac{\sigma_2}{\sigma_1}\left(p_1 - \mu_1\right)}{\sqrt{1-\rho^2}\sigma_2} = \frac{1}{\sqrt{1-\rho^2}\sigma_2}\left[\left(1 - \rho\frac{\sigma_2}{\sigma_1}\right)p_1 - \mu_2 + \rho\frac{\sigma_2}{\sigma_1}\mu_1\right],$$

and we can further rewrite the inequality above as

$$\begin{aligned}
&\Leftrightarrow p_1 - p_1\left[1 - \Phi\left(\widetilde{p}_1\right)\right] - \mathbb{E}_{p_2|p_1}\left[p_2|p_2 < p_1\right]\Phi\left(\widetilde{p}_1\right) > c \\
&\Leftrightarrow p_1 > \mathbb{E}_{p_2|p_1}\left[p_2|p_2 < p_1\right] + \frac{c}{\Phi(\widetilde{p}_1)} \\
&\Leftrightarrow p_1 > \mu_2 + \rho\frac{\sigma_2}{\sigma_1}\left(p_1 - \mu_1\right) - \sqrt{1-\rho^2}\sigma_2\frac{\phi(\widetilde{p}_1)}{\Phi(\widetilde{p}_1)} + \frac{c}{\Phi\left(\widetilde{p}_1\right)} \\
&\Leftrightarrow \sqrt{1-\rho^2}\sigma_2\left(\widetilde{p}_1 + \frac{\phi\left(\widetilde{p}_1\right)}{\Phi\left(\widetilde{p}_1\right)}\right) > \frac{c}{\Phi\left(\widetilde{p}_1\right)} \\
&\Leftrightarrow \widetilde{p}_1\Phi\left(\widetilde{p}_1\right) + \phi\left(\widetilde{p}_1\right) > \frac{c}{\sqrt{1-\rho^2}\sigma_2}
\end{aligned}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the probability density function (PDF) and cumulative distribution function (CDF) of the standard normal distribution, respectively. Since the left-hand side of the inequality ranges between 0 and $+\infty$ and increases in $\widetilde{p}_1$, which in turn increases in $p_1$ provided that $\rho < \sigma_1/\sigma_2$, we conclude that there exists a threshold $\widetilde{p}_1^*$ such that the consumer continues searching if and only if $\widetilde{p}_1 > \widetilde{p}_1^*$, or equivalently $p_1 > p_1^*$, where

$$\widetilde{p}_1^* \Phi\left(\widetilde{p}_1^*\right) + \phi\left(\widetilde{p}_1^*\right) = \frac{c}{\sqrt{1-\rho^2}\sigma_2}, \quad p_1^* = \frac{1}{1-\rho\frac{\sigma_2}{\sigma_1}}\left(\sqrt{1-\rho^2}\sigma_2 \widetilde{p}_1^* + \mu_2 - \rho\frac{\sigma_2}{\sigma_1}\mu_1\right).$$

Intuitively, the higher the observed price $p_1$, the more likely the consumer will get a better price $p_2$ from searching on platform 2, and the larger the expected extra saving in the paid price. When the observed price $p_1$ is at the reserve price $p_1^*$, the expected extra saving coincides with the extra search cost $c$. As the observed price $p_1$ continues to rise, the expected extra saving exceeds the extra search cost, and the consumer chooses to price compare on platform 2. The price comparison rate in this scenario is thus

$$R_1 = 1 - \Phi\left(\frac{p_1^* - \mu_1}{\sigma_1}\right).$$

Alternatively, if the consumer searches on platform 2 first with probability $(1-\delta)$, there exists a reserve price $p_2^*$ which can be similarly derived, such that she will price compare on platform 1 if and only if $p_2 > p_2^*$, and the price comparison rate in this scenario is

$$R_2 = 1 - \Phi\left(\frac{p_2^* - \mu_2}{\sigma_2}\right).$$

The overall price comparison rate expected for the representative consumer is thus

$$R = \delta R_1 + (1-\delta) R_2.$$

Because we take prices and consumer search costs as exogenous, we can think of the expected price comparison rate $R$ as a function of prices and search costs, or $R(\mu, \mathbf{\Sigma}, c)$, where $\mu$ and $\mathbf{\Sigma}$ are the mean and covariance matrix of the price distribution (as described above), and $c$ gives the search costs on the two platforms. Further recall that, by assumption, we have $c = vt$, where $v$ is the consumer's "value" or opportunity cost of time in hours, and $t$ is the time in hours it takes to search on either platform, and thus we can also express $R$ as a function of $v, t$, and the price parameters, or $R(\mu, \mathbf{\Sigma}, v, t)$.

# 4 Results

## 4.1 Calibration Strategy

In Section 3, we described how to compute the expected consumer price comparison rate $R(\mu, \mathbf{\Sigma}, v, t)$ under our model, given fixed assumptions for prices (i.e. $\mu, \mathbf{\Sigma}$) and consumer search costs, $c = vt$. To calibrate our model, we require benchmark estimates for price distribution parameters (call these $\mu^*$ and $\mathbf{\Sigma}^*$), consumer search costs (call these $c^* = v^*t^*$), and the rate of price comparison (call this $R^*$). With such values in hand, we can compare the expected price comparison rate (at the benchmark values), denoted $R(\mu^*, \mathbf{\Sigma}^*, v^*, t^*)$, to the observed benchmark price comparison rate, $R^* = 0.161$, as presented in Section 2.3.

We start with benchmark estimates for consumer search costs, which requires us to make estimates on both $v$, the consumer's opportunity cost or "value" of time (VOT), and $t$, the time it takes to retrieve a price quote.

To develop a benchmark for $v$, we refer to several recent papers from the economics literature which use revealed preference approaches to estimate mean VOTs for populations similar to the one in our study. These studies along with their estimated mean VOT benchmarks are displayed in Table A1. While these VOT benchmarks may not perfectly match our focal population, they provide a reference point for our calibration exercise. To develop a single "preferred" VOT benchmark value, we take the average of the three recent mean VOTs (adjusted to November 2023 dollars[5].) detailed in column (3) of Table A1; this yields a preferred benchmark value of $v^* = \$28.80$. In addition, our calibration will present results for a range of possible values of $v$ from \$5 to \$100 to examine how implied price comparison rate changes under different assumptions about VOTs.

Turning to the parameter $t$, or the time it takes to collect a price quote, our calibration will again present results for a range of possible values, from $t = 10$ seconds to $t = 5$ minutes, showing how the implied value of $R(\mu, \mathbf{\Sigma}, v, t)$ changes. To fix ideas, we take $t^* = 1$ minute as our preferred benchmark. Recall that the time to retrieve a price quote is assumed to be the same on either platform as noted in Section 3.

To derive benchmark estimates for price distribution parameters, we use the means, standard deviations, and correlation coefficients of the empirical bi-variate distribution of Uber and Lyft rides for each equal-weighted quintile group of trip length in our audited sample, as presented in section 2.2. An implied price comparison rate $R$ can thus be derived for each group, and the aggregated price comparison rate for the entire sample would thus be the average of all five group's price comparison rates.

[5]We adjust to November 2023 dollars as this is starting month of our Comscore data, as noted in Section 2.3

Intuitively (and later confirmed in our calibration results), the implied price comparison rate $R$ changes monotonically as either $v^*$ or $t^*$ increases, and thus our calibration strategy further allows us to back out implied values of $v$ (or $t$) through a binary search, assuming $t$ fixed at $t^*$ (or $v$ fixed at $v^*$) and the price comparison rate $R$ coincides with the observed price comparison rate $R^*$.

## 4.2 Calibration Results

Figure 3 shows the overall results from our calibration exercise from two different perspectives.

In Panel A of Figure 3, each row of the table corresponds to one of the key parameters from our theoretical model setup. The "Benchmark Value" column of the table gives the preferred benchmark estimates for each parameter, whereas the "Implied Value" column shows the implied value of the parameter from our calibration exercise, fixing all other parameters at their benchmark levels.

For example, the first row of the table shows that the benchmark value for the price comparison rate from the Comscore data was 0.161, whereas the implied value from the calibration was 0.972. In other words, if the representative consumer has a value of time of $v^* = \$28.80$ and takes $t^*$=1 minute to check the price, we expect that she should be opening both apps to compare prices around 97.2% of the time (fixing the price distribution parameters), which is substantially above the 16.1% we observe in the Comscore data. Likewise, the second row shows that our benchmark VOT is $v^* = \$28.80$ based on estimates from recent economics literature; however, to rationalize the level of price comparison that we observe in the Comscore data (i.e. $R^* = 0.161$), our model implies that consumers would need to be valuing their time at \$209.47 per hour (again fixing $t^*$=1 minute and the price distribution parameters), again substantially higher than our benchmark. Finally, if we instead fix consumers' VOT at the benchmark level of $v^* = \$28.80$ and the price distribution parameters, our model suggests consumers would need to spend 7.27 minutes to retrieve a rideshare price quote to rationalize the price comparison rate of $R^* = 0.161$ from the Comscore data.

Panel B shows the implied aggregate price comparison rate $R$ for a range of potential values for consumer search cost parameters $v$ and $t$. To generate these estimates, we fix the calibrated parameters of the price distribution (i.e. $\mu$ and $\Sigma$) at the benchmark values observed in the price data for each group as described in section 2.2. The horizontal line in the plot labeled $R^*$ indicates the observed price comparison rate in the Comscore data described in section 2.3 ($R^* = 0.161$); the vertical line labeled $v^*$ is our "preferred" benchmark for VOT, as described in section 4.1 ($v^* = \$28.80$). As also indicated in 4.1, our preferred benchmark for $t$ is 1 minute (indicated as $t^*$).

Note that some values presented in Panel A can theoretically be "read off" of Panel B. For example, the implied value of $R$ in Panel A is given by the $y$-value of the intersection point of the $v^*$ vertical line and the light-green "$t$ =1 minute" line in Panel B. Likewise, the implied value of $v$ is given by the $x$-value of the intersection point of the $R^*$ horizontal line and the "$t$ =1 minute" line (which in this case would happen beyond the truncated x-axis of the figure).

# 5 Discussion

Our audit reveals considerable price dispersion for identical rides between Uber and Lyft, with an average gap of roughly 14 percent—even though comparing prices requires little more than opening a second app. To shed further light on this pattern, we use a simple sequential search model calibrated to observed behavior.

Reconciling the observed dispersion with the low rate of price comparison—only 16.1 percent of riders who open one platform also open the other—would require implausibly high values of either the value of time or the time it takes to check a second app. The results suggest that even small sources of friction, such as app design, information frictions, or hassle costs, are sufficient to sustain substantial price differences and limit competitive pressure. These patterns imply that the modest search barriers in ridesharing markets are profitable for platforms but reduce potential gains to consumers.

A back-of-the-envelope calculation based on our audit and usage data suggests that New York City riders collectively forgo roughly $300 million in potential annual savings—about six percent of total gross bookings—by not comparing prices between the two platforms. Such foregone savings illustrate how even thin frictions in digital markets can meaningfully shape the distribution of surplus between consumers and firms.

Finally, platform policies may further entrench these frictions. For example, Uber's API explicitly prohibits "using the Uber API to offer price comparisons of third-party services,"[6] limiting the emergence of automated tools that could reduce search costs. Together, these findings show that small barriers to comparison can weaken effective competition and shift surplus toward platforms.

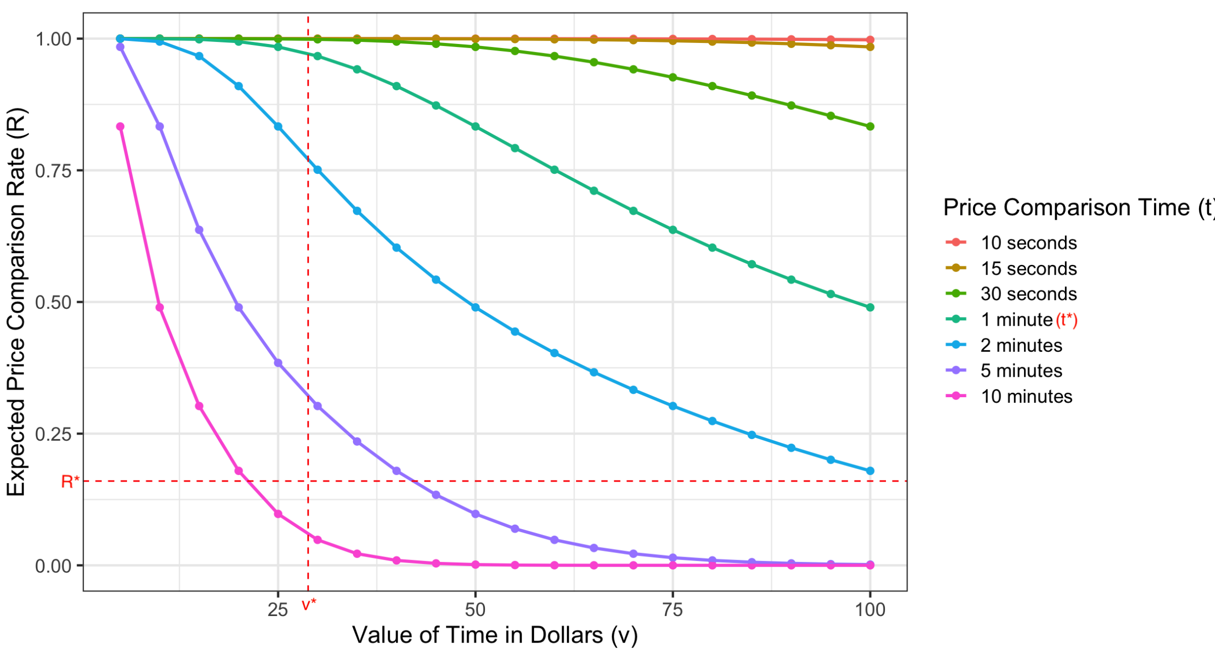
[6]See Figure A12 and A13 for screenshots of relevant clauses in the Uber API Terms of Use.

Figure 3: Results from Calibration Exercise

Panel A: Benchmark and Implied Parameter Values

| Model Parameter | Benchmark Value | Implied Value |
|---|---|---|
| Price comparison rate ($R$) | 0.161 | 0.972 |
| Value of time ($v$); hourly | \$28.80 | \$209.47 |
| Time to search ($t$) | 1 min. | 7.27 min. |

Panel B: Expected Price Comparison Rate ($R$) by $v$ and $t$




*Notes: This figure presents results from the calibration exercise described in Section 4. Panel A reports benchmark and implied values for the key parameters. The source of the benchmark values is described in Section 4.1. Panel B shows the expected level of price comparison (R) implied by the model described in Section 3 for a range of possible values for t and v. The benchmark values, denoted* $v^*, t^*$ *and* $R^*$ *are likewise indicated on the chart.*

Table 2: Estimate of potential savings from price comparison in New York City

| # | Quantity | Feb 2024 | All 2024 | Source |
|---|---|---|---|---|
| (1) | Rideshare trips | 16,574,610 | 202,731,430 | NYC TLC Data |
| (2) | Gross booking volume | $411,871,469.89 | $5,319,777,470.75 | NYC TLC Data |
| (3) | Price comparison rate | 0.16 | 0.16 | Comscore data |
| (4) | Avg. gain from comparing prices (starting on Uber) | $1.92 | $1.92 | Price audit data |
| (5) | Avg. gain from comparing prices (starting on Lyft) | $1.61 | $1.61 | Price audit data |
| (6) | Percent of consumers starting on Uber | 54% | 54% | Comscore data |
| **(7)** | **Total savings available from price comparison** | **$24,746,157.92** | **$302,681,268.69** | **Computed from above** |
| **(8)** | **Price comparison savings as percent of gross booking volume** | **6.01%** | **5.69%** | **Computed from above** |

*Notes: This table estimates the aggregate effect of consumer price comparison behavior on gross booking volume in New York City. "Gross booking volume" represents the total amount paid by customers including fares, fees, and taxes, but excluding tips. The "price comparison rate" indicates the share of consumers who compare prices between platforms before booking. The "average gain from comparing prices" is estimated from our price audit data as the average of the difference in price between the platforms when the second platform is cheaper, or zero otherwise.*

# References


**Argente, David, Doireann Fitzgerald, Sara Moreira, and Anthony Priolo**, "How do entrants build market share? The role of demand frictions," *American Economic Review: Insights*, 2025, *7* (2), 160–176.

**Bakos, J Yannis**, "Reducing buyer search costs: Implications for electronic marketplaces," *Management science*, 1997, *43* (12), 1676–1692.

**Baye, Michael R, John Morgan, and Patrick Scholten**, "Price dispersion in the small and in the large: Evidence from an internet price comparison site," *The Journal of Industrial Economics*, 2004, *52* (4), 463–496.

**_ , _ , and _** , "Information, search, and price dispersion," *Handbook on economics and information systems*, 2006, *1*, 323–375.

**Bergemann, Dirk and Alessandro Bonatti**, "Markets for information: An introduction," *Annual Review of Economics*, 2019, *11* (1), 85–107.

**Blake, Tom, Sarah Moshary, Kane Sweeney, and Steve Tadelis**, "Price salience and product choice," *Marketing Science*, 2021, *40* (4), 619–636.

**Brown, Jeffrey R and Austan Goolsbee**, "Does the Internet make markets more competitive? Evidence from the life insurance industry," *Journal of political economy*, 2002, *110* (3), 481–507.

**Brynjolfsson, Erik and Michael D Smith**, "Frictionless commerce? A comparison of Internet and conventional retailers," *Management science*, 2000, *46* (4), 563–585.

**Buchholz, Nicholas, Laura Doval, Jakub Kastl, Filip Matejka, and Tobias Salz**, "The Value of Time: Evidence from Auctioned Cab Rides," *Econometrica: Journal of the Econometric Society*, 2025, pp. 929–958.

**Burdett, Kenneth and Kenneth L Judd**, "Equilibrium price dispersion," *Econometrica: Journal of the Econometric Society*, 1983, pp. 955–969.

**Diamond, Peter A**, "A model of price adjustment," *Journal of economic theory*, 1971, *3* (2), 156–168.

**Ellison, Glenn and Alexander Wolitzky**, "A search cost model of obfuscation," *The RAND Journal of Economics*, 2012, *43* (3), 417–441.

**_ and Sara Fisher Ellison**, "Search, obfuscation, and price elasticities on the internet," *Econometrica*, 2009, *77* (2), 427–452.

**Ghose, Anindya, Avi Goldfarb, and Sang Pil Han**, "How is the mobile Internet different? Search costs and local activities," *Information Systems Research*, 2013, *24* (3), 613–631.

**Goldszmidt, Ariel, John A List, Robert D Metcalfe, Ian Muir, V Kerry Smith, and Jenny Wang**, "The value of time in the United States: Estimates from nationwide natural field experiments," 2020.

**Kohn, Meir G and Steven Shavell**, "The theory of search," *Journal of Economic Theory*, 1974, *9* (2), 93–123.

**Lyft, Inc.**, "Lyft's Fourth Quarter and Full Year 2023 Results," `https://s27.q4cdn.com/263799617/files/doc_financials/2023/q4/02/Lyft-2023-12-31-Press-Release-Annual.pdf` 2023. Accessed: 2024-02-20.

**Lyft, Inc.**, "Lyft Reports Record Q4 and Full-Year 2024 Results," `https://investor.lyft.com/news-and-events/news/news-details/2025/`

Lyft-Reports-Record-Q4-and-Full-Year-2024-Results/default.aspx February 2025.

**Mattia, Andrea**, "The Distribution of Value of Time: An Analysis from Traffic Congestion and Express Lanes," 2023. Job Market Paper.

**McCall, John Joseph**, "Economics of information and job search," *The Quarterly Journal of Economics*, 1970, *84* (1), 113–126.

**Rob, Rafael**, "Equilibrium price distributions," *The Review of Economic Studies*, 1985, *52* (3), 487–504.

**Salop, Steven and Joseph E Stiglitz**, "The theory of sales: A simple model of equilibrium price dispersion with identical agents," *The American Economic Review*, 1982, *72* (5), 1121–1130.

**Scott-Morton, Fiona, Florian Zettelmeyer, and Jorge Silva-Risso**, "Internet car retailing," *The Journal of Industrial Economics*, 2001, *49* (4), 501–519.

**Stahl, Dale O**, "Oligopolistic pricing with sequential consumer search," *The American Economic Review*, 1989, pp. 700–712.

**Stigler, George J**, "The economics of information," *Journal of political economy*, 1961, *69* (3), 213–225.

**Uber Technologies, Inc.**, "Uber Announces Results for Fourth Quarter and Full Year 2023," https://investor.uber.com/news-events/news/press-release-details/2024/Uber-Announces-Results-for-Fourth-Quarter-and-Full-Year-2023/default.aspx 2024. Accessed: 2024-02-20.

**Uber Technologies Inc.**, "Uber Q4 2024 Earnings Supplemental Data," https://s23.q4cdn.com/407969754/files/doc_earnings/2024/q4/supplemental-info/Uber-Q4-24-Earnings-Supplemental-Data.pdf 2025.

**U.S. Bureau of Labor Statistics**, "CPI Inflation Calculator," https://www.bls.gov/data/inflation_calculator.htm 2023.

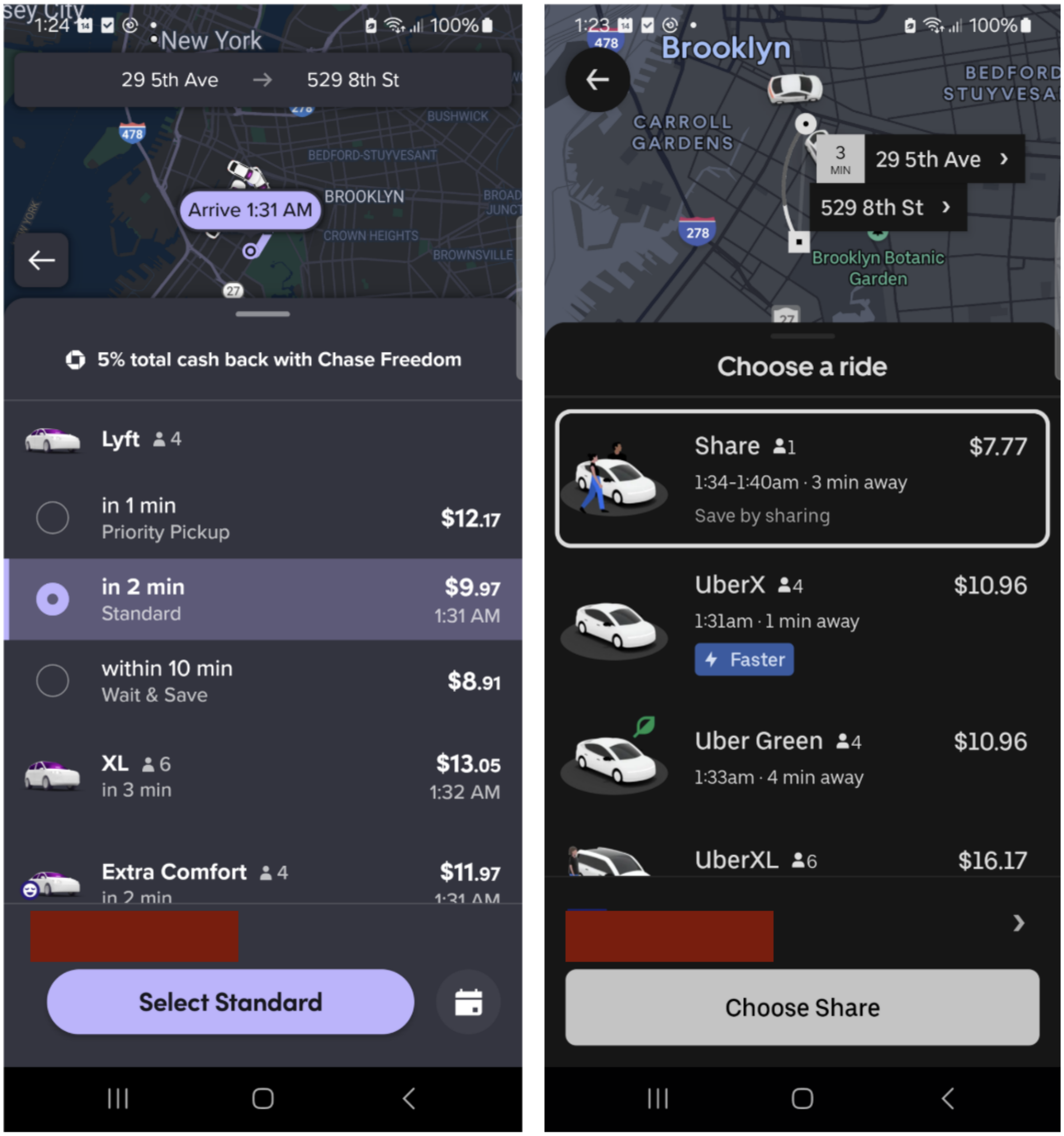
# A Appendix

Table A1: Recent Value of Time (VOT) Benchmarks

| Paper (1) | Mean VOT (2) | Adjusted to Nov. 2023 (3) | Study Dates (4) | Study Pop. (5) |
|---|---|---|---|---|
| Goldszmidt et al. (2020) | \$19.38 (1.39) | \$25.16 (1.80) | Dec 2015-Jan 2016 | Lyft rideshare passengers in 9 US cities |
| Buchholz et al. (2025) | \$13.47 (0.4) | \$17.13 (0.51) | Sep 2016-June 2018 | Liftago rideshare passengers in Prague. |
| Mattia (2023) | \$35.02 | \$44.12 | Mar 2017-Apr 2018 | Highway drivers in Minneapolis-St. Paul. |

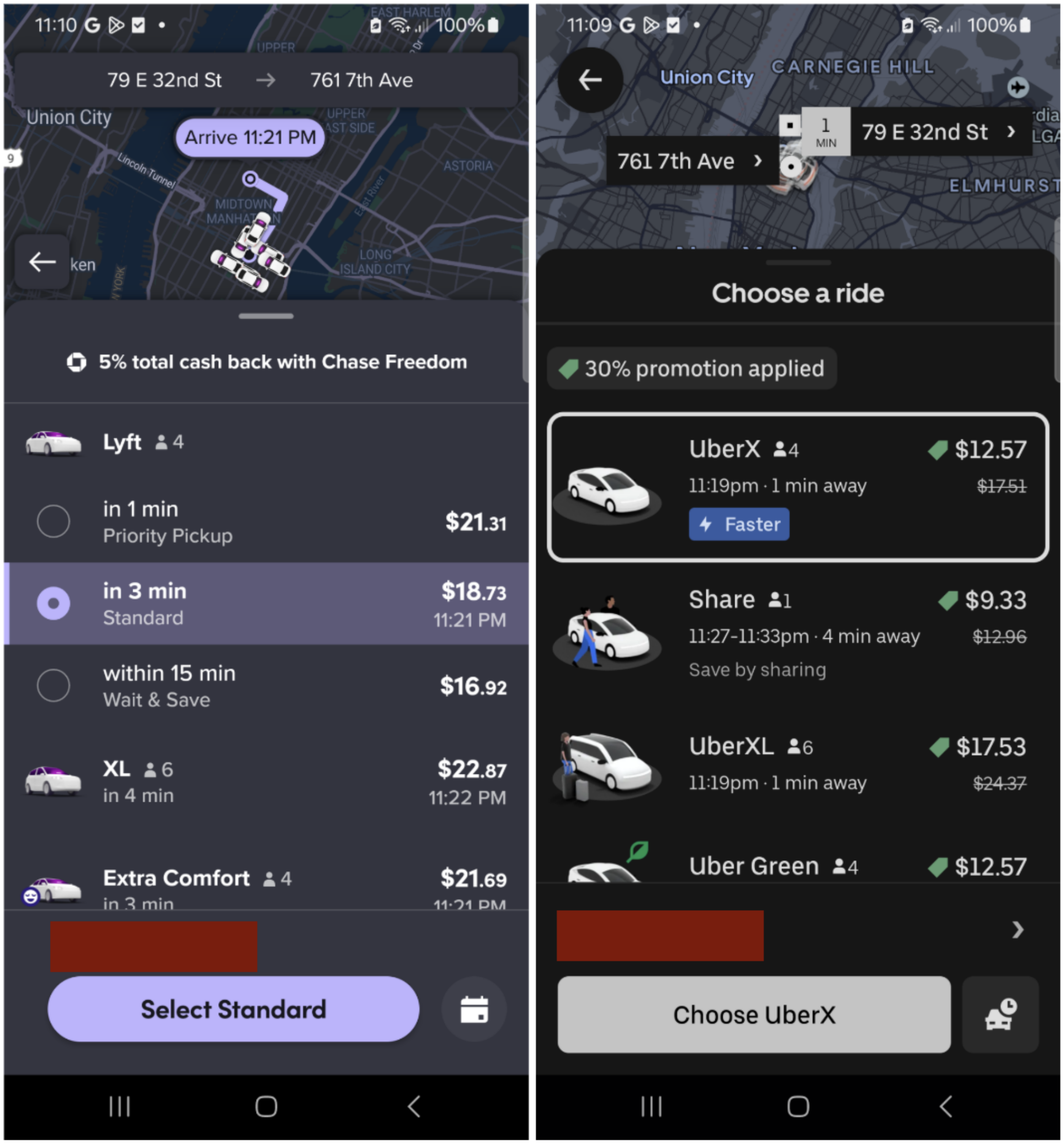
*Notes: This table displays mean value of time (VOT) estimates from three recent papers from the economics literature. Adjusted to Nov 2023 dollars from the earliest date of the reported data collection in the paper, using the BLS online CPI inflation calculator U.S. Bureau of Labor Statistics (2023). The mean reported for Mattia (2023) is from his estimation of the the VOT distribution for* ***all*** *drivers, discussed in section 4, and displayed in Figure 12 of his paper. Note that this is distinct from his higher RDD estimate, which is estimated on the population of express lane drivers only (vs. all drivers), who Mattia shows appear to have a higher VOT than all drivers (but are policy-relevant in his setting).*

Figure A1: Screenshot of Uber and Lyft Applications from Price Audit



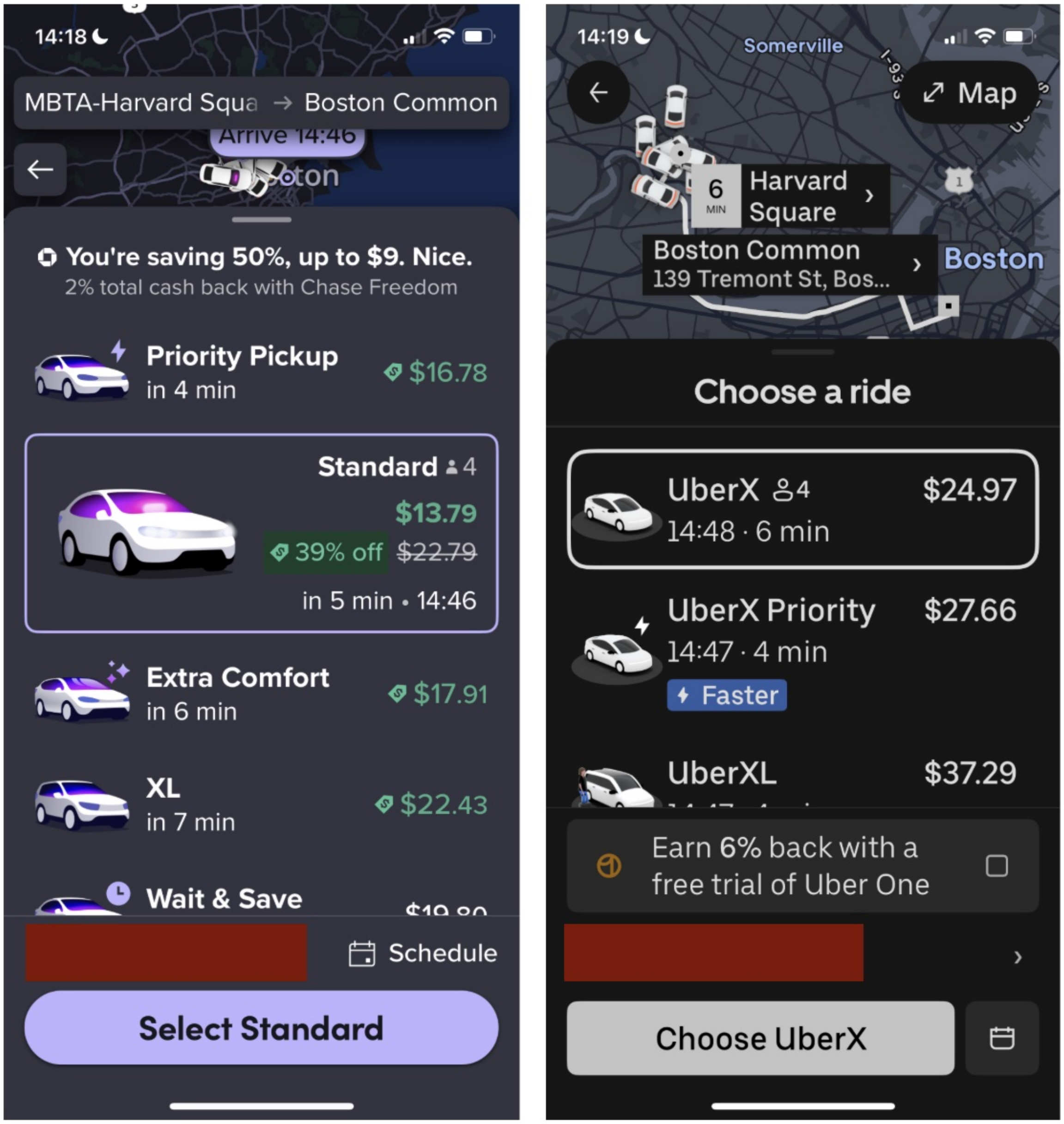

*Notes: This figure shows screenshots of the interface for observing price and wait time on Lyft (left) and Uber (right) for a matched trip collected during our audit of rideshare prices described in Section 2.2.*

Figure A2: Example of Uber Discount from Audit Account



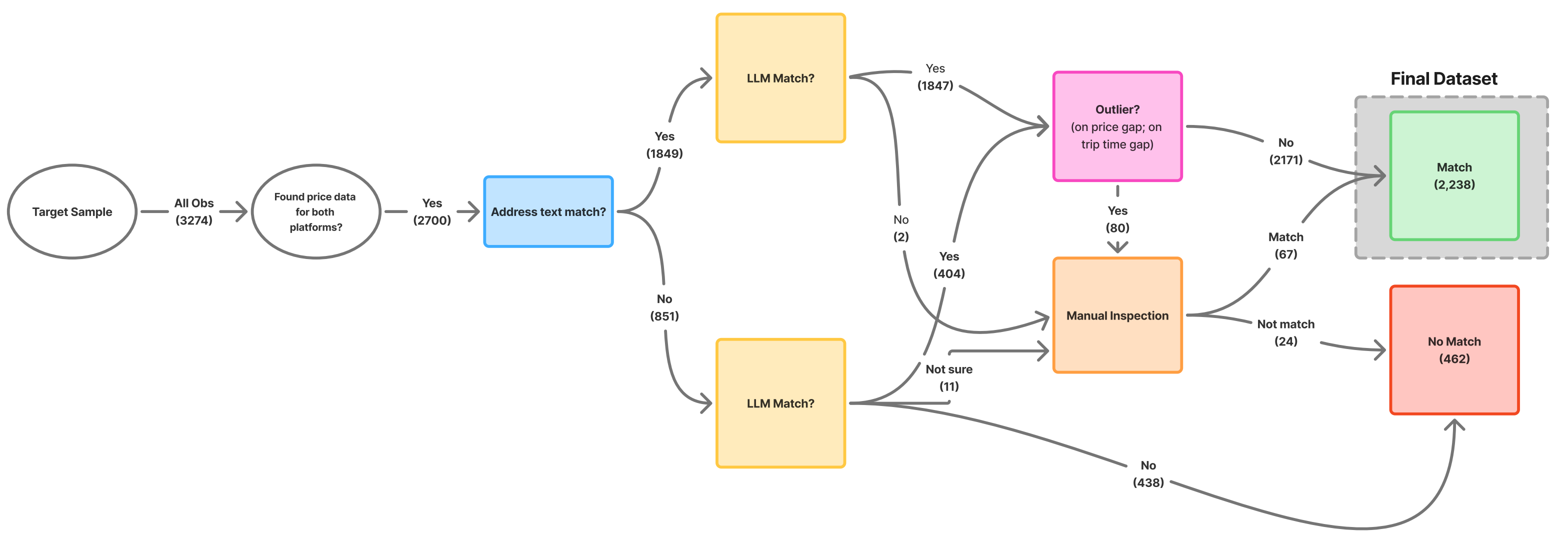

*Notes: This figure shows an example of a pair of screenshots from our price audit that includes a promotional discount on Uber of the sort that was common in our audit. When excluding discounts, we use the crossed-out UberX price (in this case, \$17.51) as the Uber fare. Note that marked down price only approximately matches the the quoted 30% promotion:* $1 - (12.57/17.51) \approx 28.2\%$*; this is possibly due to the inclusion of other non-discountable fees and taxes in the prices displayed.*

Figure A3: Example of Lyft Discount from Personal Account



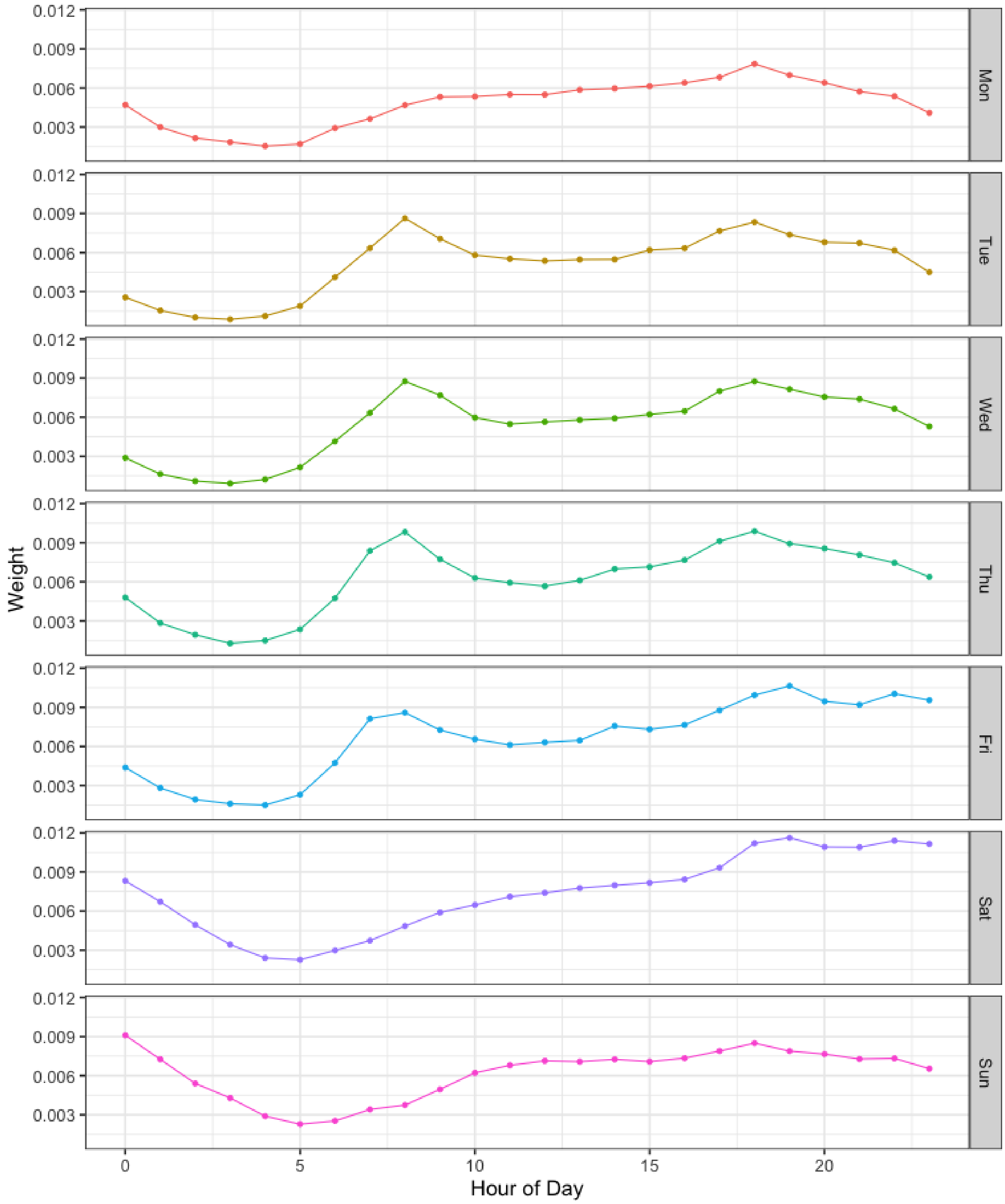

*Notes: This figure shows an example of a discount offering from Lyft but not Uber for one of the author's personal rideshare accounts for a trip in the Boston area.*

Figure A4: Data Cleaning Process Outline



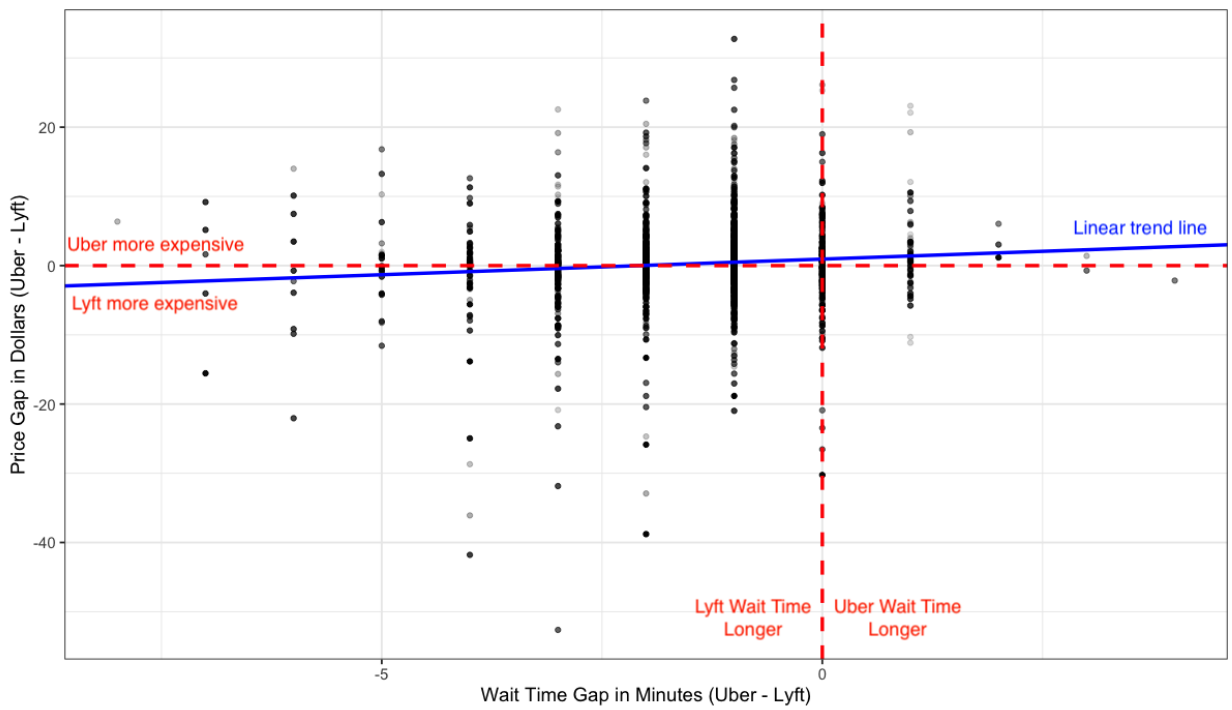

*Notes: This figure outlines the data cleaning process described in 2.2. Numbers in parentheses indicate the count of observations proceeding through each step of the process. "Address text match" means that standardized origin and destination strings both match exactly across platforms. "LLM match" means that a large language model determined that observations on both platforms were a match after being provided with raw audit data and screenshots. "Outlier" means that the observation was at least 3 standard deviations from the mean on either signed price gap or the difference in expected trip time across the platforms (a useful signal that the trips may be mismatched)*

Figure A5: Line Plot of Weights for each Hour-of-Week Cell



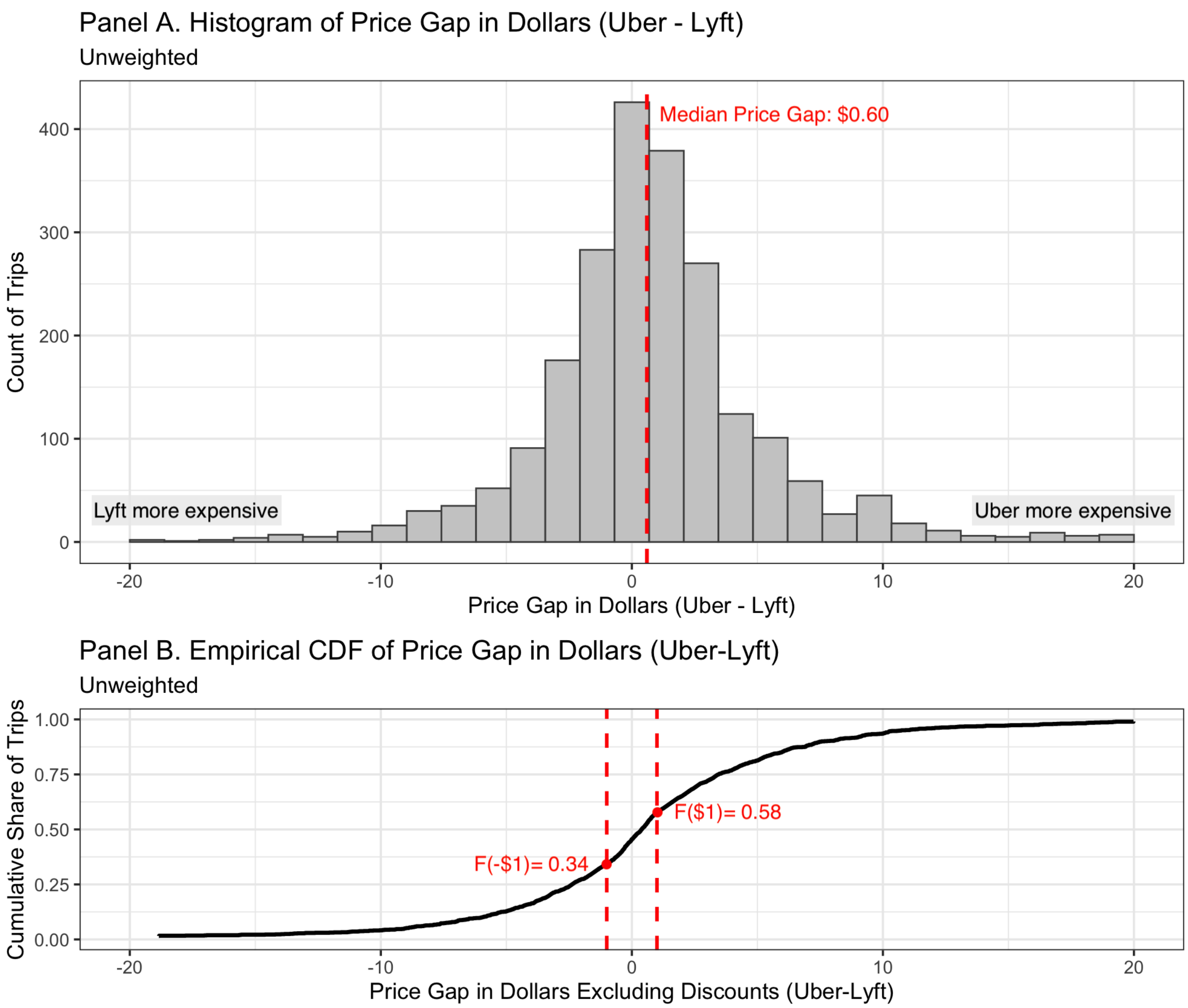

*Notes: This figure displays the weights used in the main exhibits to adjust for the stratified sampling scheme. These weights are generated by computing the share of total rideshare trips taken in each hour-of-week cell in the reference week of the NYC TLC trip data (February 15, 2024 to February 21, 2024).*

Figure A6: Price Gap vs. Wait Gap (Uber - Lyft)



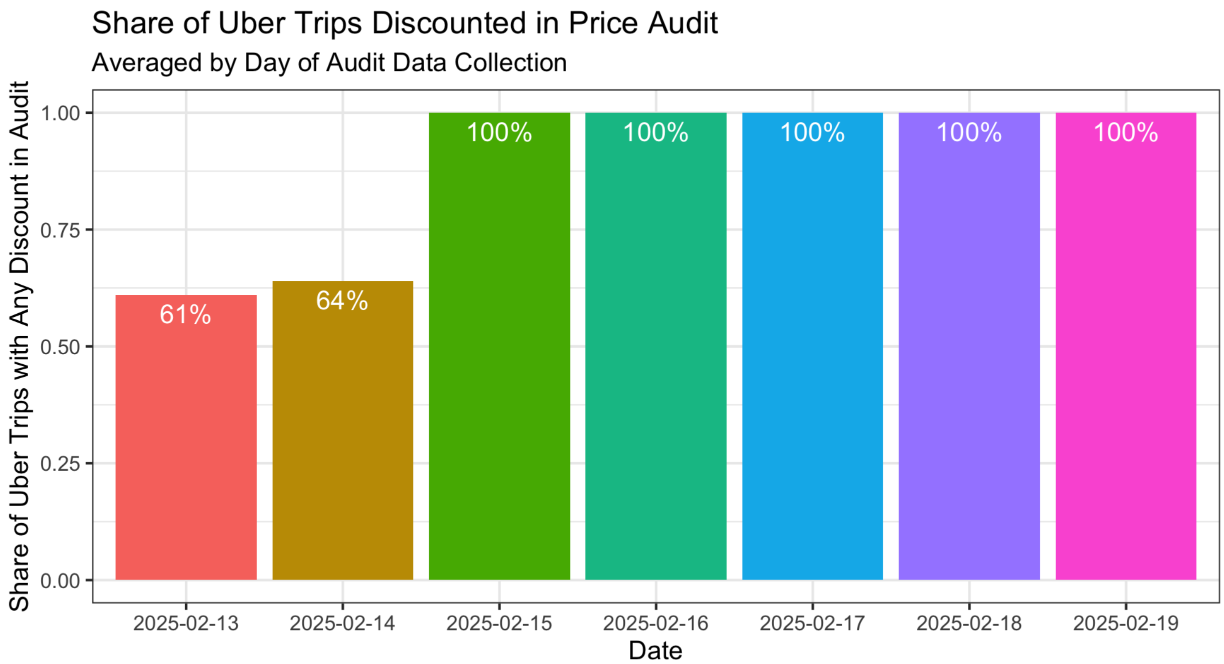

*Notes: This figure plots $WaitGap_j$ vs. $PriceGap_j$ as defined in section 2.2. Point transparency corresponds to the weight of the corresponding point. The linear trend line overlaid is from a weighted regression of $PriceGap_j$ on $WaitGap_j$ and indicates that there is a positive correlation between the two quantities in our sample.*

Figure A7: Price Dispersion Between Uber and Lyft for Identical Trips (Unweighted)



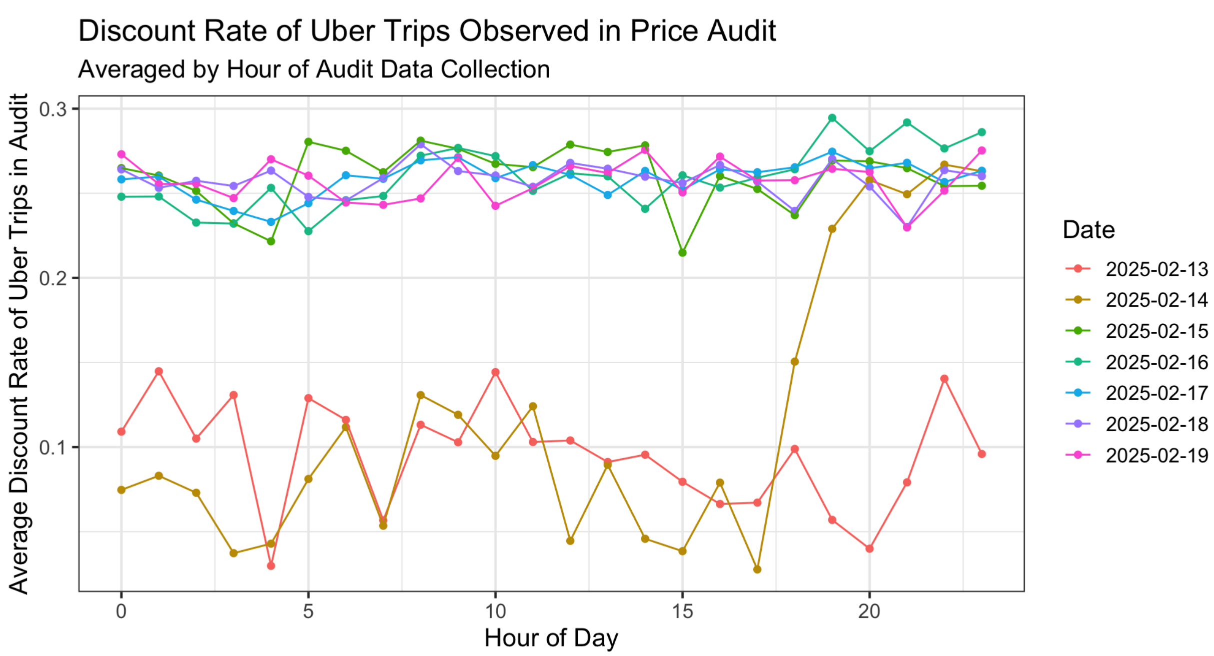

*Notes: This figure shows the distribution of* $PriceGap_j = Price_{Uber,j} - Price_{Lyft,j}$ *as defined in section 2.2.2 excluding promotions and discounts. Panel A is a histogram. Panel B is a empirical CDF. This figure matches Figure 1 but is not weighted to adjust for stratified sampling.*

Figure A8: Share of Uber Trips Discounted in Price Audit



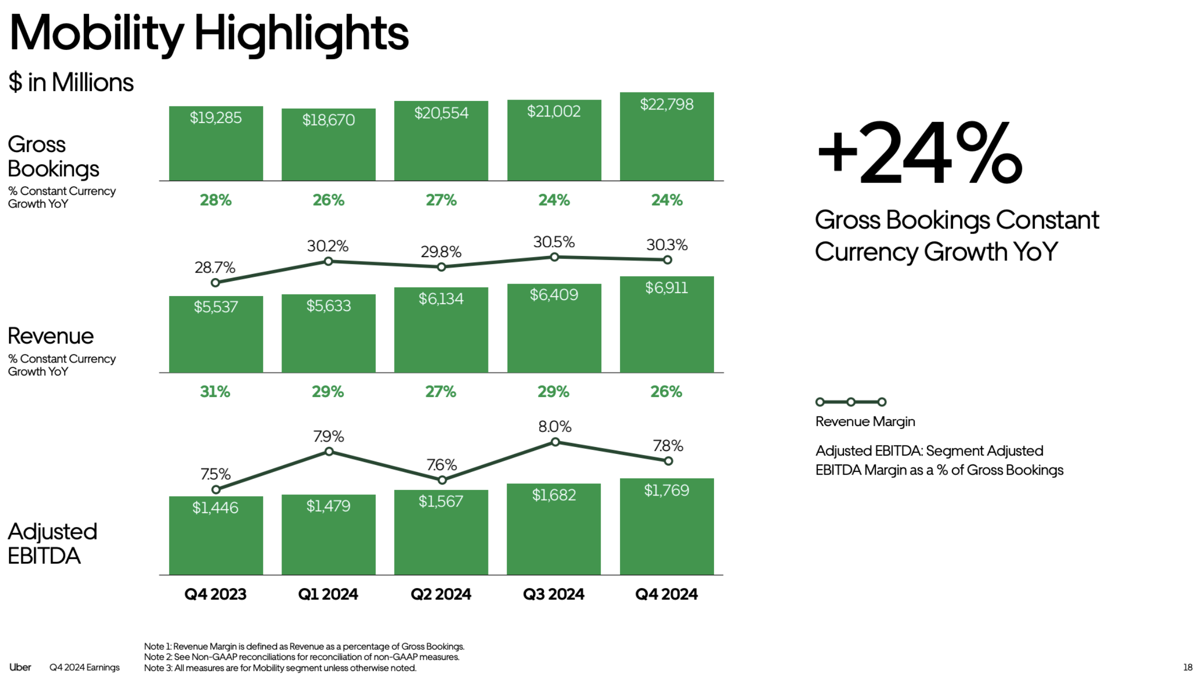

*Notes: This figure shows the share of Uber trips in our price audit sample that included a discount from Uber, grouped by day of the audit.*

Figure A9: Discount Rate of Uber Trips Observed in Price Audit




*Notes: This figure shows the average rate of discounts observed for Uber trips in the audit sample, by hour of the audit. This rate pools all trips in the corresponding segment, regardless of whether the trip includes a discount.*

Figure A10: Screenshot from Uber 2024 Earnings Reporting Supplement




*Notes: This is a screenshot of Uber's financial reporting for its Mobility offerings; see Uber Technologies Inc. (2025)*

Figure A11: Screenshot from Lyft 2024 Earnings Reporting

**Financial and Operational Results through the Fourth Quarter of 2024**

| | Three Months Ended | | | Year Ended December 31, | |
|---|---|---|---|---|---|
| | Dec. 31, 2024 | Sept. 30, 2024 | Dec. 31, 2023 | 2024 | 2023 |
| | (in millions, except for percentages) | | | | |
| Active Riders | 24.7 | 24.4 | 22.4 | | |
| Rides | 218.5 | 216.7 | 190.8 | 828.3 | 709.0 |
| Gross Bookings | $ 4,278.9 | $ 4,108.4 | $ 3,724.3 | $ 16,099.4 | $ 13,775.2 |
| Revenue | $ 1,550.3 | $ 1,522.7 | $ 1,224.6 | $ 5,786.0 | $ 4,403.6 |
| Net income (loss) | $ 61.7 | $ (12.4) | $ (26.3) | $ 22.8 | $ (340.3) |
| Net income (loss) as a percentage of Gross Bookings | 1.4% | (0.3)% | (0.7)% | 0.1% | (2.5)% |
| Net cash provided by (used in) operating activities | $ 153.4 | $ 264.0 | $ 43.5 | $ 849.7 | $ (98.2) |
| Adjusted EBITDA | $ 112.8 | $ 107.3 | $ 66.6 | $ 382.4 | $ 222.4 |
| Adjusted EBITDA margin (calculated as a percentage of Gross Bookings) | 2.6% | 2.6% | 1.8% | 2.4% | 1.6% |
| Adjusted Net Income | $ 114.5 | $ 118.1 | $ 71.1 | $ 391.5 | $ 250.7 |
| Free cash flow | $ 140.0 | $ 242.8 | $ 14.9 | $ 766.3 | $ (248.1) |

Note: Information on our key metrics and non-GAAP financial measures are also available on our Investor Relations page.

*Notes: This is a screenshot of Lyft's financial reporting; see Lyft (2025)*

Figure A12: Prohibition on Using Uber API for Price Comparison

## GET /estimates/price

**Access to this API endpoint requires approval from Uber.**

As part of Uber's ongoing privacy improvements, we're changing our Developer API program with new access policies for third party applications.

Please contact your Uber Business Development representative or Uber point of contact to get access to this API.

**Please ensure that your use of this API endpoint complies with the API Terms of Use.** Using the Uber API to offer price comparisons with competitive third party services is in violation of **§ II B** of the **API Terms of Use**. Please make sure that you familiarize yourself with the API Terms of Use to avoid losing access to this service.

*Notes: This is a screenshot from the website for the Uber Pricing API (https://developer.uber.com/docs/riders/references/api/v1.2/estimates-price-get); collected September 24, 2025.*

Figure A13: Section III (G) of Uber API Terms of Use

### G. Certain Prohibited Uses.

Unless permitted by applicable law or any Supplemental Agreement(s) between you and Uber, you will not, and will not direct, encourage, or assist any other party to: (a) license, sublicense, sell, resell, transfer, assign, distribute or otherwise provide or make available to any other party the Uber API Services; (b) modify or make derivative works based upon the Uber API Services; (c) improperly use the Uber API Services, including (1) creating Internet "links" to any part of the Uber API Services, "framing" or "mirroring" any part of the Uber API Services on any other websites or systems, or "scraping" or otherwise improperly obtaining data from the Uber APIs, (2) transmitting any viruses or other code that may damage, detrimentally interfere with, surreptitiously intercept or expropriate any system or data; (d) reverse engineer, decompile, modify, or disassemble the Uber API Services; (e) send spam or otherwise duplicative or unsolicited messages with the Uber APIs; or (f) use the Uber APIs to (1) display any offensive content or any content for which you do not have the right to share with Uber or to display or (2) distribute unsolicited advertising or promotions, or (3) engage in fraudulent or unauthorized activity including phishing, pharming, spidering, harvesting or other similar activities.

In addition, you shall not, and shall not direct, encourage, or assist any other party to, access or use the Uber API Services to: (a) design or develop a competitive or substantially similar product or service; (b) copy or extract any features or functionality thereof; (c) launch or cause to be launched on or in connection with the Uber API Services a malicious automated program or script, including web spiders, crawlers, robots, indexers, bots, viruses or worms, or any program intended to overburden or hinder the operation and/or performance of the Uber API Services; (d) attempt to gain unauthorized access to the Uber API Services or its related systems or networks; (e) include any underlying Uber platform or product with competitors in any aggregated view i.e. webpage, app, software, etc.; (f) aggregate Uber's data with competitors' data; or (g) parse or scrape any of Uber's data; in each case other than as explicitly permitted by Uber in writing. You will not share with a third party (or enable a third party to use) any operational, technical or other data obtained through the use of the Uber API Services in any manner that is competitive to Uber, including, without limitation, in connection with any application, website or other product or service that also includes, features, endorses, or otherwise supports in any way a third party that provides services competitive to Uber's products and services.

*Notes: This is a screenshot from the terms of use of the Uber API (https://developer.uber.com/docs/riders/terms-of-use); collected September 24, 2025.*