Leaving Money on the Dashboard: Price Dispersion and Search Frictions on Uber and Lyft

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Research Questions

- Do consumers compare prices between Uber and Lyft?
- How large is the potential gain from doing so?
- What are the aggregate consequences?

What we do in this paper

We do four things:

1. **Price dispersion**: measure using a novel synchronized audit of Uber and Lyft prices for representative sample of NYC rideshare trips.
2. **Price comparison behavior**: benchmark observed rates of consumer price comparison between rideshare apps using device-level Comscore data.
3. **Implied search costs**: infer by developing & calibrating a simple sequential search model using benchmarks from our data (& some additional assumptions).
4. **Aggregate savings**: conduct a back-of-the-envelope calculation of the aggregate savings available from more price comparison (partial equilibrium).

Preview of results

What do we find?

1. **Price dispersion:** For identical NYC trips, the mean absolute Uber–Lyft price gap is $\approx$ \$3.53, about **14%** of the average fare.
2. **Price comparison behavior:** Only $\approx$ 16% of device-days with any rideshare activity show both Uber and Lyft opened.
3. **Implied search costs:** based on calibration exercise, we find...
   - We would expect far more comparison ($\sim$ 97%) than we observe ($\sim$ 16%) based on benchmark value of time estimates.
   - Alternatively: consumers behave as though they value time at $\approx$ \$210 per hour.
4. **Aggregate savings:** Combining these facts with NYC volumes implies riders leave roughly $\sim$ \$300M per year on the table ($\sim$ 6% of gross bookings) by not comparing.

Background: Friction in the digital economy

- Early promise: toward frictionless search (Bakos (1997), Brynjolfsson and Smith (2000)).
- Yet frictions persist; worsened by firm behavior:
  - Ellison and Ellison (2009) — obfuscation and costly attention.
  - Blake et al. (2021) — drip pricing in digital markets.
- Mobile app environment? (Ghose et al. (2013))
- This paper: price dispersion and price comparisons across competing platforms in mobile app environment.

Setting: Rideshare market

Rideshare is a useful setting to study price comparison behavior because:

- Large, economically important, two-platform market: NYC rideshare ($\sim$ 200M trips and $\sim$ \$5.3B in gross bookings in 2024).
- Relatively homogeneous service with upfront pricing
- Dynamic pricing means consumers need to check to know prices
- Once both apps are installed, price comparison is technologically simple (open second app, enter trip, see price).

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Rest of this presentation: walk through each of these pieces in turn.

(1) Measuring price dispersion in rideshare

To estimate price dispersion for a typical rideshare consumer in NYC:

- Conduct a novel synchronized audit of Uber and Lyft prices for a representative sample of NYC rideshare trips, based on historical rideshare trip data from the NYC Taxi & Limousine Commission (TLC).
- Measure price dispersion using the distribution of price gaps between Uber and Lyft for identical trips (indexed by j):

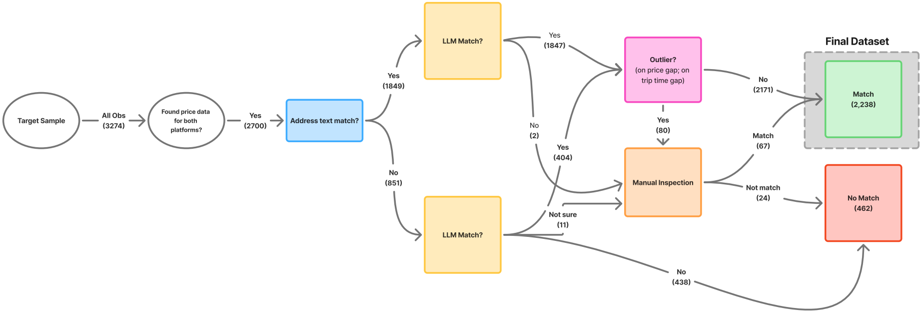
$$\text{PriceGap}_j = \text{Price}_{\text{Uber},j} - \text{Price}_{\text{Lyft},j}$$

(1) Measuring price dispersion in rideshare (cont.)

Details of the audit process:

1. **Build 'reference' sample**: Use NYC TLC trip records to build a 'reference' sample of NYC rideshare trips over course of one week (same week as audit, one year prior); stratified by hour-of-week to maximize data collection.
2. **Convert reference sample to queryable trips**: (1) rejection sampling random (lat,lon) points within Taxi Zones & matching on trip length (w/in 0.5 miles of reference), then (2) reverse-geocoding to get searchable addresses.
3. **Collect price & wait time quotes**: For each audit trip, collect price & wait time quotes from both Uber and Lyft apps on a single Android device using new accounts over course of week, using custom software.
    - Search at same minute of week as reference trip (e.g. 10:42 AM on Thursday)
    - Randomize which app is queried first to avoid ordering effects.
    - Focus on comparable "UberX" and "Lyft (Standard)" offerings.
4. **Extensive data cleaning**: Combine LLM, automated, and manual review to ensure final trips match across apps.

(1) Measuring price dispersion in rideshare (cont.)



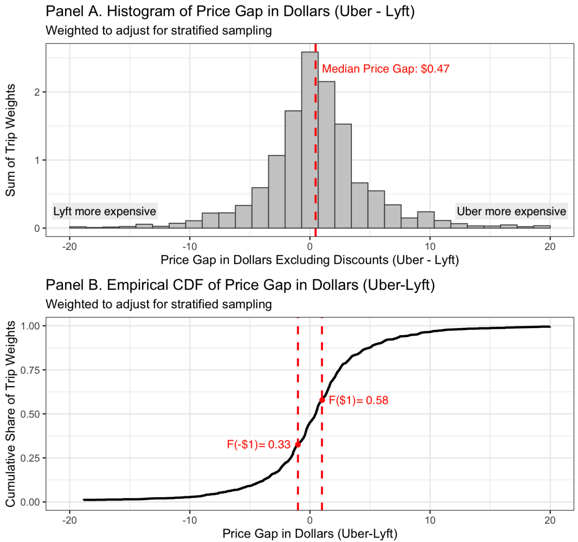
End result: 2,238 matched trip-level price and wait time quotes for "UberX" and "Lyft (Standard)" offerings from period of one week in February 2025 (excluding promotions and discounts).

(1) Measuring price dispersion in rideshare (cont.)

Important details about our price data:

- We focus on **base prices**, which we understand to be uniform across users for a given trip at a given time.
- **Limitation**: Uber and Lyft frequently offer personalized discounts and promotions that we do not observe in our audit.
  - Testing in our own apps revealed frequent discounts on both platforms.
  - In the audit, the Uber account triggered a discount on several occasions.

(1) Measuring price dispersion in rideshare (cont.)



(1) Measuring price dispersion in rideshare (cont.)

Key findings:

- Distribution of $PriceGap_j$ is relatively symmetric and centered near zero $\rightarrow$ neither platform is consistently cheaper than the other.
- Price dispersion is meaningful:
  - Average absolute gap: $\approx$ \$3.53 ($\approx$ 14% of average fare)
  - $|PriceGap_j| > \$1$ in $\approx$ 75% of trips
- Percent gap roughly constant across trip lengths $\rightarrow$ more absolute dollar gains for longer trips.
- Wait time gaps are positively correlated with price gaps $\rightarrow$ price gaps are not driven by wait time gaps (i.e. higher relative price for shorter wait times).

Together, these facts suggest potential gains from comparing prices between Uber and Lyft.

(2) Do consumers compare prices?

Benchmark price comparison behavior using Comscore mobile panel (Sep-Nov 2023):

- Opt-in panel that covers 4,016 devices observed across 91 days.
- Observe which apps are opened and when but not what user did on app
- Also observe basic demographic info (age, income etc.).

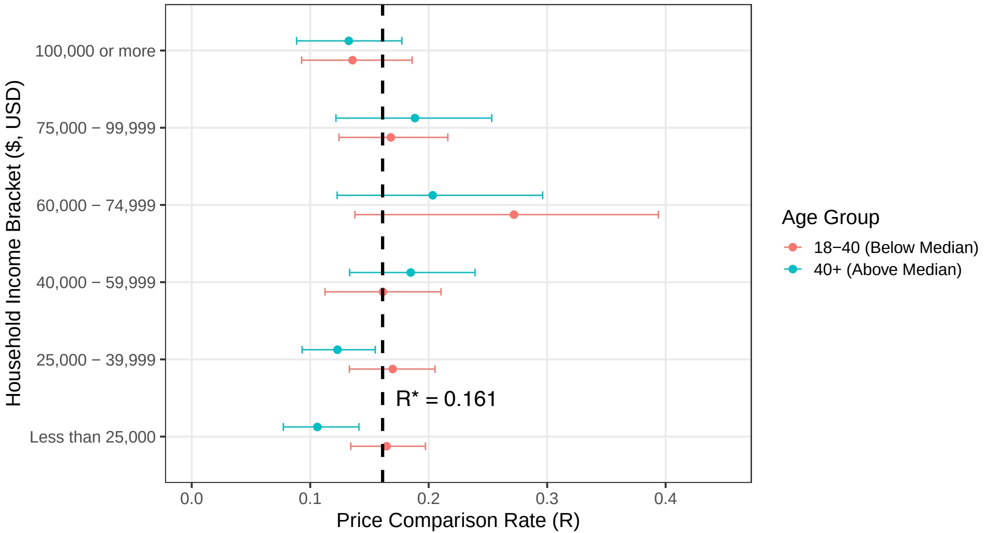
(2) Do consumers compare prices? (cont.)

- Unit of analysis: device-day. Let $\text{Uber}_{it} \in \{0, 1\}$ be an indicator for whether device i opened the Uber app at least once on day t (and Lyft_{it} analogously).
- Define price comparison rate as:

$$R = \frac{\sum_{i,t}(\text{Uber}_{it} \cdot \text{Lyft}_{it})}{\sum_{i,t} \max\{\text{Uber}_{it}, \text{Lyft}_{it}\}}$$

- Interpretation: Given that a device opened *any* rideshare app on a given day, what proportion of the time did the device open *both* rideshare apps on that day?

(2) Do consumers compare prices? (cont.)



(2) Do consumers compare prices? (cont.)

Key findings:

- Overall price comparison rate relatively low: $\approx 16\%$
- Limited systematic variation across income and age groups.

So far, have seen that consumer search is limited and price dispersion is present. Motivates two related questions:

- Are consumers searching less than we would expect? (given observed price dispersion and benchmark value of time estimates)
- What level of search costs would rationalize the observed price comparison rate? (given observed price dispersion)

To answer these questions, we develop and calibrate a simple sequential search model.

Model (based on McCall (1970) and Kohn and Shavell (1974)):

- Representative consumer chooses between two platforms offering a homogeneous product.
- Prices (p_1, p_2) are exogenous draws from a bivariate normal distribution with means μ_1, μ_2, variances σ_1^2, σ_2^2, and correlation ρ. Consumer knows joint distribution of prices but not the realized prices for a given trip, learns prices only by searching.
- Consumer observes one price at a time and pays a search cost $c = vt$ each time she opens an app, where:
  - v: value of time (opportunity cost per hour),
  - t: time required to obtain a quote in an app.
- Optimal search rule has a reserve-price structure: search the second app only when the first observed price is high enough.

Purpose: provide a simple mapping from price distribution and search parameters to an expected comparison rate $R(\mu, \Sigma, v, t)$ that we can use for benchmarking.

(3) Do consumers under-search? / Implied search costs (cont.)

What do we find?

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.

Note: Value of time benchmark is based on recent literature (Mattia (2023), Buchholz et al. (2020), Goldszmidt et al. (2020)). We assume a 1-minute time to search.

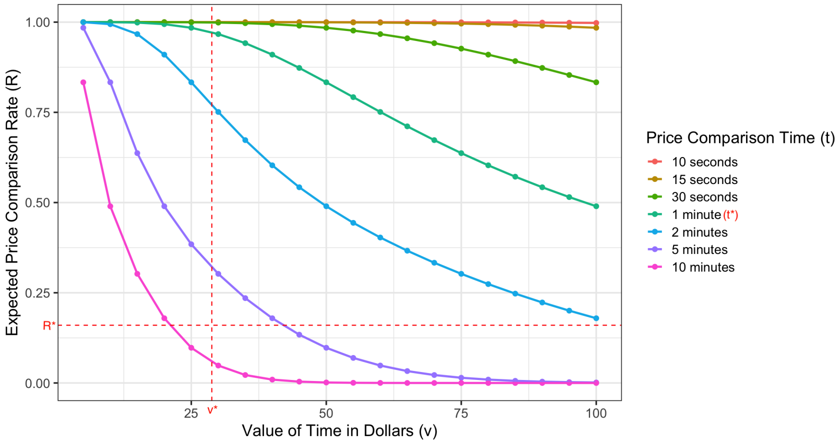


Figure: Expected comparison rate $R(\mu^*, \Sigma^*, v, t)$ by value of time and search time

(4) Aggregate savings

Back-of-the-envelope calculation of aggregate savings foregone by riders who do not compare:

- **NYC rideshare volume (2024)**: $\sim$ 200M trips; $\sim$ \$5.3B in gross bookings (fares + fees + taxes, excluding tips).
- **Average gain from comparison**: $\approx$ \$1.7 per trip among non-comparers, combining audit-based gaps with starting-platform shares.
- **Observed comparison rate**: $R^* = 0.161$; most trips do not involve cross-app comparison.
- **Implied annual savings foregone**: $\sim$ \$300M ($\sim$ 6% of gross bookings) left on the table by riders who do not compare in NYC.

Conclusion

Recap:

- Considerable price dispersion between Uber and Lyft for identical trips.
- Limited price comparison by consumers despite low switching costs.
- Frictions are modest at the individual level, but create significant losses to consumers in aggregate.
- Aggregators could help, but limited by platform policies (e.g. Uber API terms of service).

Takeaways:

- Small frictions can meaningfully shape the distribution of surplus between consumers and platforms—even in markets where comparison is easy.
- A broader challenge of the digital age: abundant information, but limited attention.

Thank You!

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