On Ridesharing Competition and Accessibility: Evidence from Uber, Lyft, and Taxi

Shan Jiang, Le Chen, Alan Mislove, Christo Wilson

Northeastern University

Outline

- Background
- Data collection
- Results on competition and accessibility

Background: Why study ridesharing?

Ridesharing is shifting Vehicle for Hire (VFH) market.

- The Treasurer Office of SF estimates that there are over 45,000 Uber and Lyft drivers (2016);
- The SF Municipal Transportation Agency has issued only 2,026 taxi medallions;
- In the New York City, Uber and Lyft cars are now estimated to outnumber taxis 4 to 1 (2016).

	Taxi	Uber / Lyft
Price	Fixed by law	Set by company
Accessibility	Required to serve the entire city	No requirement
Data	Providing data report	Mostly no detailed data shared

Ridesharing is NOT transparent! -> Auditing?

Background: Auditing is hard

Uber Shares Its Data with the City of Boston

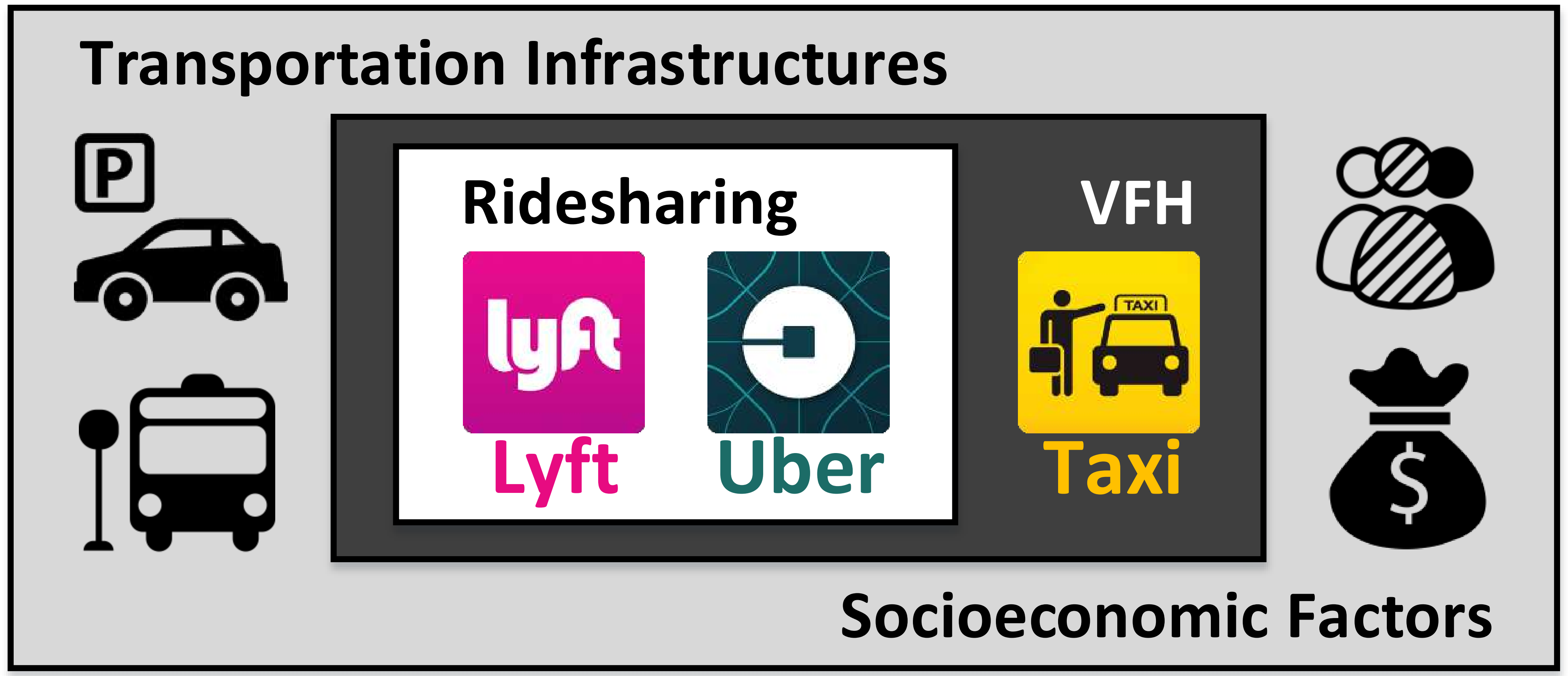
by **STEVE ANNEAR** • *1/13/2015, 11:40 a.m.*

Highly touted Boston-Uber partnership has not lived up to hype so far

By Adam Vaccaro June 16, 2016

Only share highly aggregated data, cannot be used for analysis.

Background: What do we care?



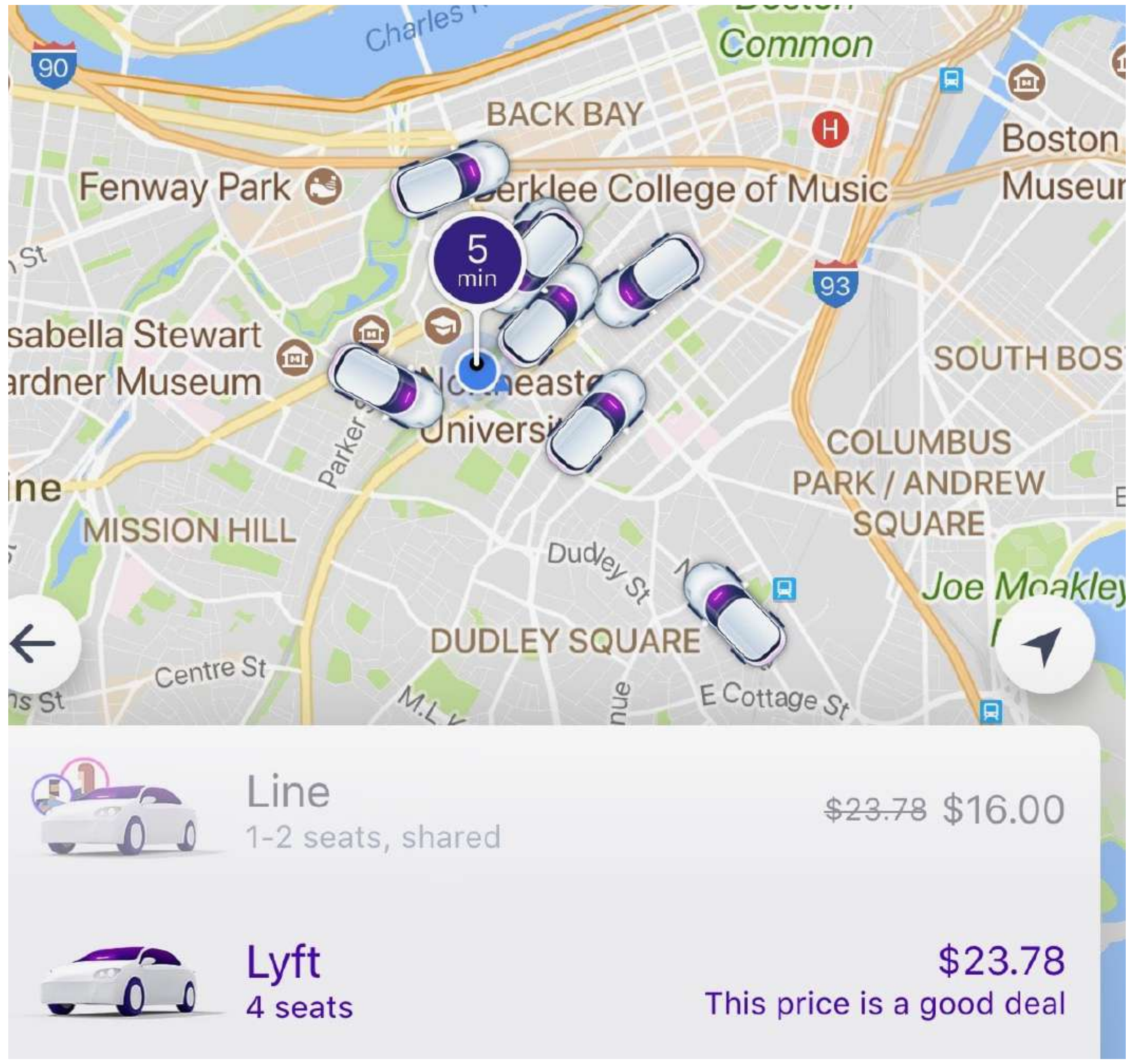
Competition:

- Competition between Uber and Lyft (ridesharing market);
- Competition between ridesharing (Uber and Lyft) and taxis (VFH market).

Accessibility:

- Citywide factors (population, transportation, etc);
- Potential algorithmic discrimination (diverse neighborhood, low-income area, etc).

Data collection: Analysis of mobile traffic




```
{
    timestamp: 1523482986,
    surge_multiplier: 1.2,
    estimate_waiting_time: 60,
    nearby_cars: [
        {
            car_id: 0000001,
            locations: [ (timestamp1, lng1, lat1), (timestamp2, lng2, lat2), …]
        },
        ……
        {
            car_id: 000008,
            locations: [ (timestamp1, lng1, lat1), (timestamp2, lng2, lat2), …]
        }
}
```

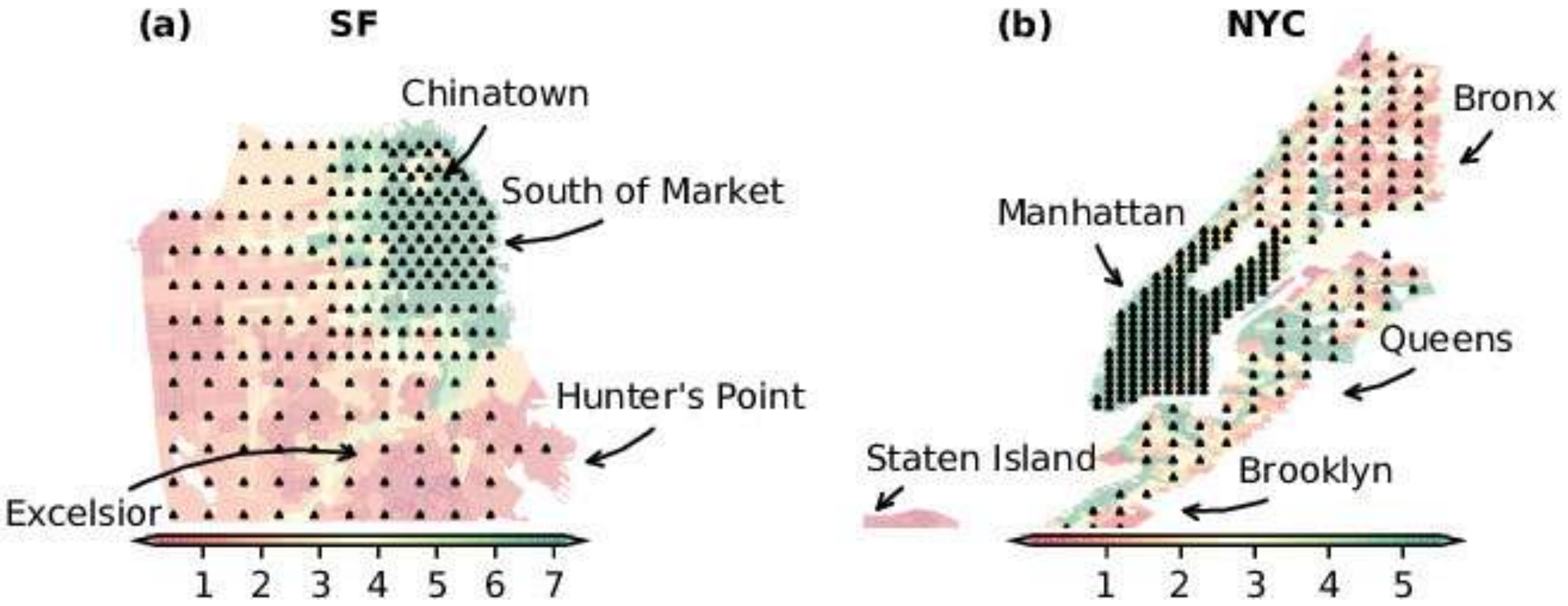

You see a map with:

- price;
- estimated waiting time;
- 8 nearby cars.

Your phone sees a JSON encoded data traffic with:

- current surge multiplier;
- estimated waiting time;
- timestamped trajectories of GPS locations of 8 nearby cars.

Data collection: "Blanketing" cities



"Blanketing" cities with emulated users to collect data.

- Fully covered SF, covered most part of NYC;
- Records data every 5 seconds;
- Nov 12 - Dec 22, 2016 in SF, Feb 1 to Feb 27, 2017 in NYC for Uber and Lyft;
- Collaborated with SFCTA to get taxi data Nov 1 - Dec 30, 2017.

Data collection: **Ethics**

NO personal information collected.

- All identifiers are opaque IDs.

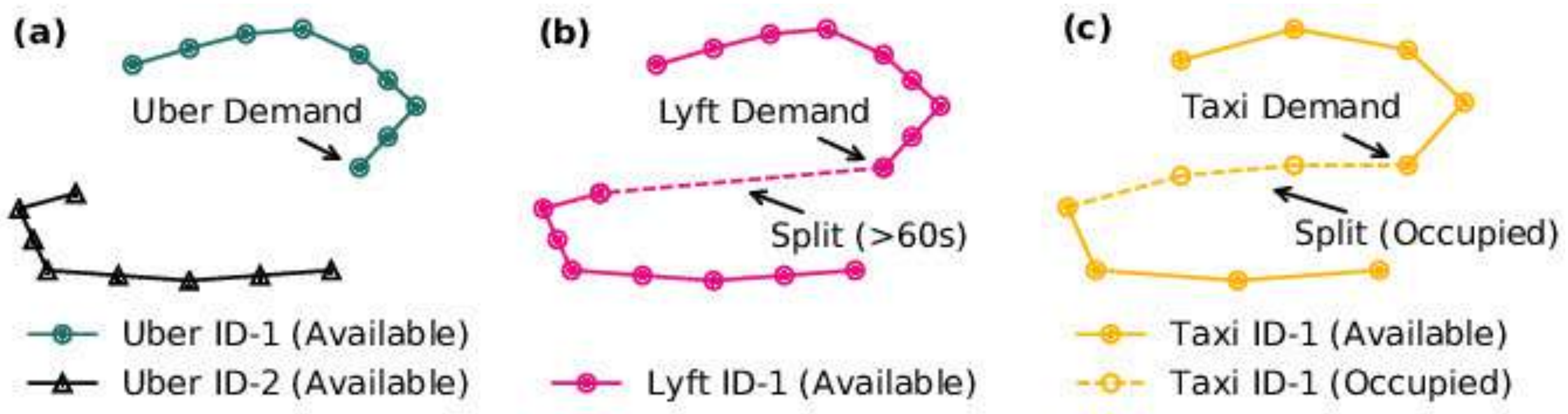
NO impact on ridesharing platforms, drivers or riders.

- We only observed nearby cars, and never requested any actual rides;
- Our infrastructure has the same behavior as ordinary smartphone apps.

Positive impact on the society.

- SFCTA report: http://www.sfcta.org/tncstoday
- Visualization: http://tncstoday.sfcta.org
- Regulation in process…

Data preprocessing: Inferring supply and demand



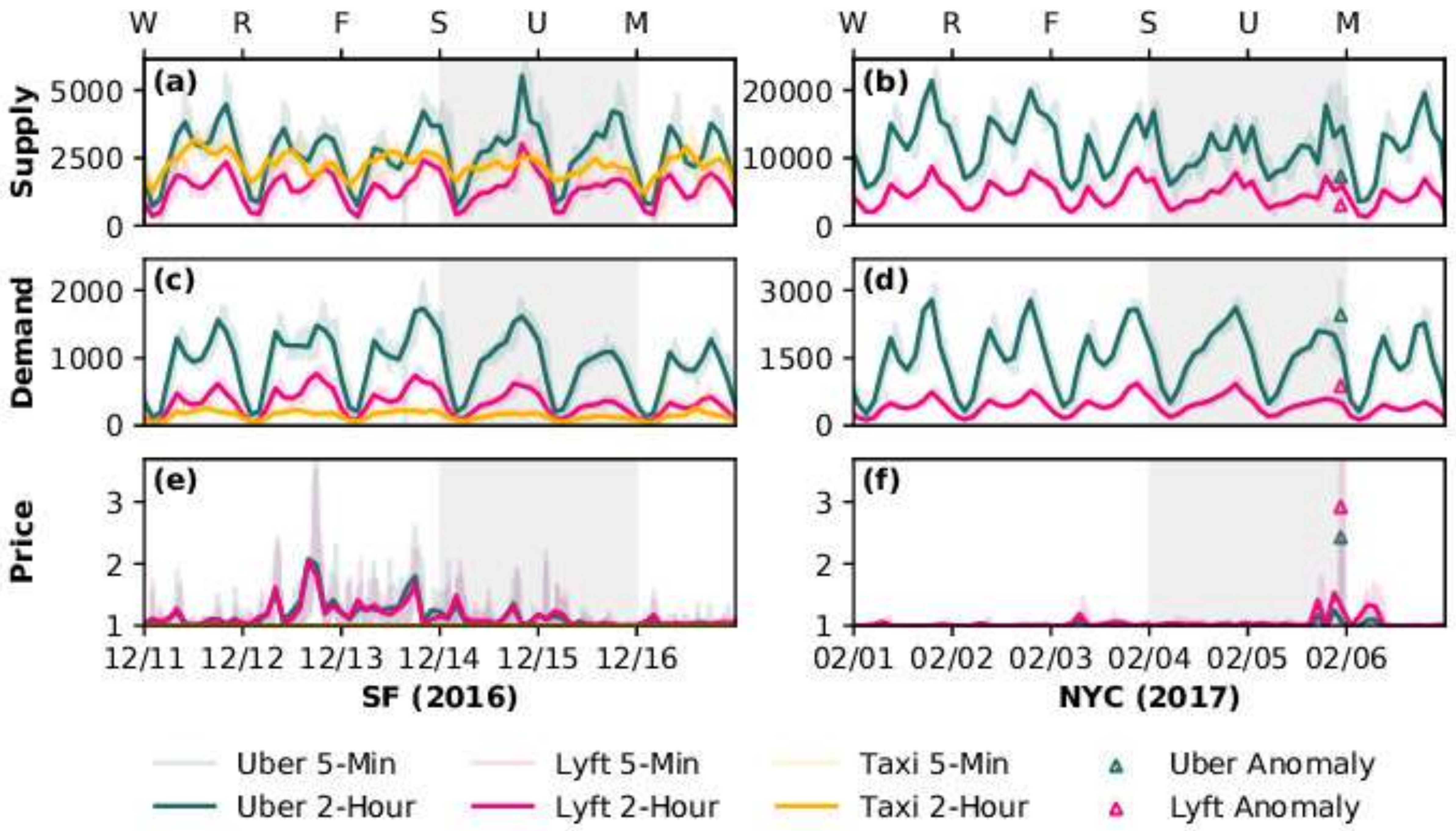
Aggregate data to get index of market features (block-group level, 5-minute window).
- **Supply**: the number of available cars;
- **Demand**: the number of disappearing cars;
- **Price**: the average price;

* More details in our paper.

Temporal analysis: Daily pattens

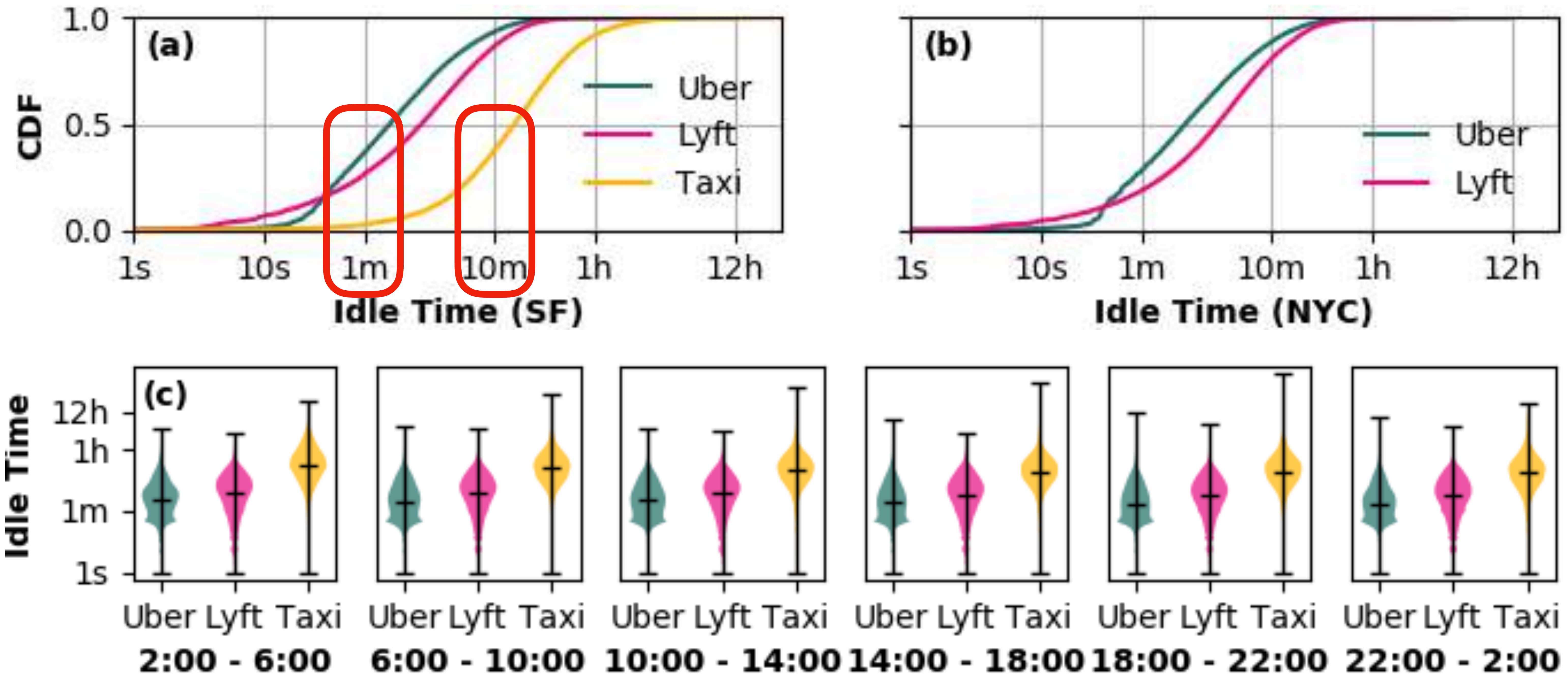
Daily patterns:
- Supply and demand patterns are similar;
- 2 peaks on weekdays and 1 peak on weekends;

Between Uber and Lyft:
- Uber has 2× more supply and demand than Lyft;
- Supply is similar (SF: r=.90***, NYC r=.91***);
- Demand is similar (SF: r=.94***, NYC r=.92***);
- Price is similar (SF: r=.82***, NYC r=.89***).



Between ridesharing (Uber and Lyft) and taxis:
- Taxi supply is between Uber and Lyft at daytime but more at night. But demand is much lower;
- Supply patterns are less similar (Uber/Taxi: r=.53***, Lyft/Taxi: r=.53***);
- Demand patterns are less similar (Uber/Taxi: r=.62***, Lyft/Taxi: r=.58***).

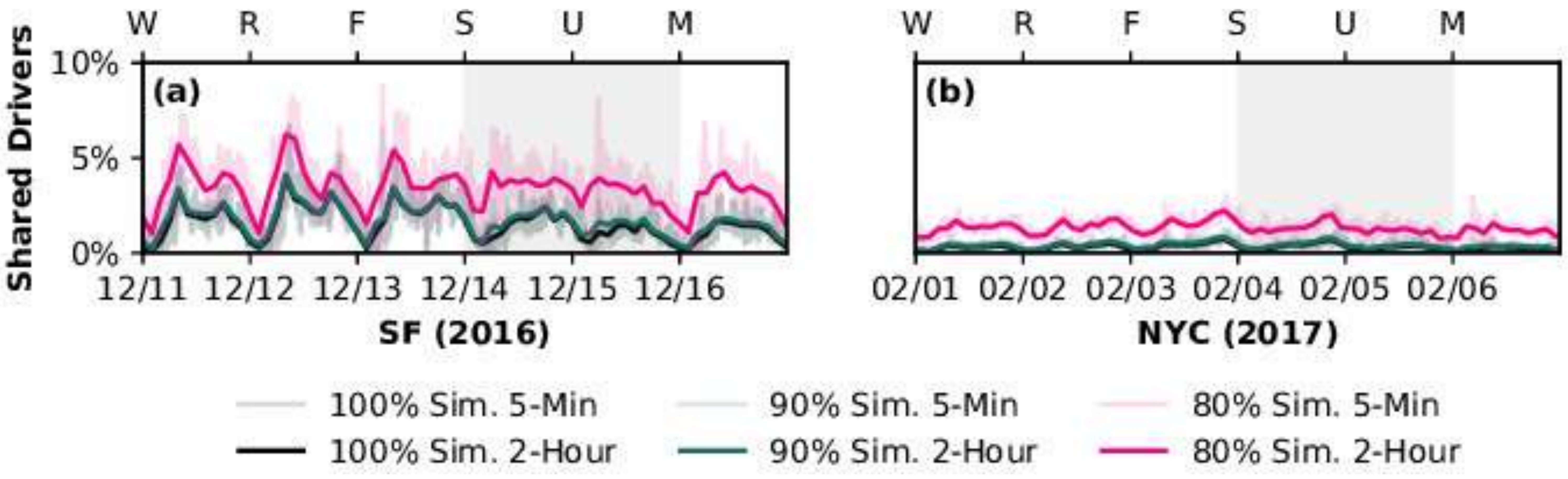
Temporal analysis: Utilization rate



Utilization rate of Uber, Lyft and taxis drivers:

- Uber and Lyft drivers spend on average ~1 minute idling;
- Taxi drivers spend on average ~10 minutes idling;
- This finding holds when we examine the distribution over different time of a day.

Temporal analysis: "Shared" drivers

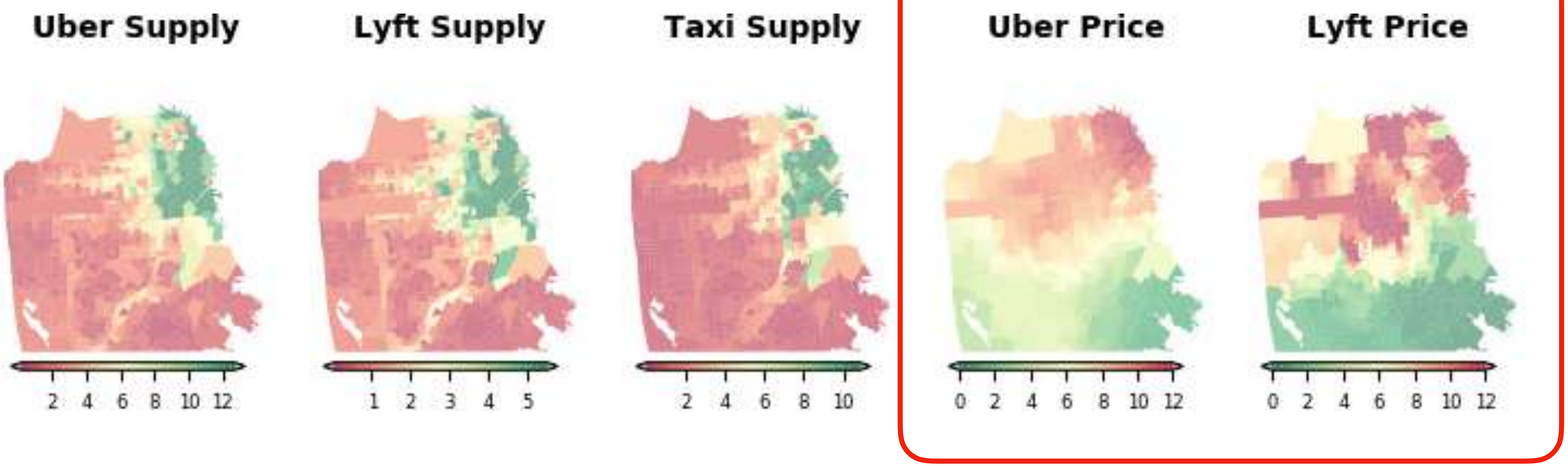


"Shared" drivers that work for Uber and Lyft at the same time:

- Detect such driver if there are "similar" trajectories in both Uber and Lyft data;
- "Similar": Appearing at similar time, GPS locations are similar, and disappear at similar time;
- Under most conservative estimation, ~1.5% in SF and ~0.5% in NYC.

* More details in our paper.

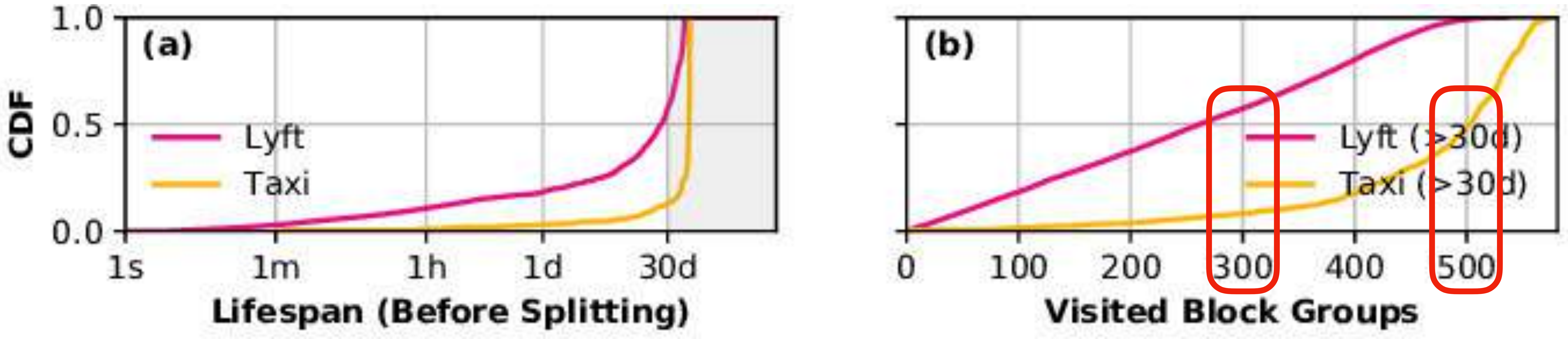
Spatial analysis: Distribution in cities



Spatial patterns:

- Supply and demand patterns are similar (not shown in the figure, r>.80***);
- For supply and demand, Uber, Lyft and taxis are similar (r>.80***);
- For price, Uber and Lyft are less similar (SF: r=.67***, NYC r=.57***).

Spatial analysis: A peek at accessibility



How many block-groups has a “full-time” driver visited?

- “Full-time”: Appearing in our data for more than 30 days;
- Assumption: Full-time drivers should have ample time to serve the majority part of the city;
- Mean visited block-groups: 261 for Lyft (~45% of SF), 503 for taxis (~87% of SF);

This does NOT mean that Lyft is serving only half of the city.

Accessibility: What do we care?

Transportation infrastructures:

- Public transit stops, on-street parking meters, off-street parking lots, etc.
- Civil engineering perspective, how ridesharing interact with existing infrastructure?
- Good control variables.
- Data sources: Open data platforms of SF and NYC, Department of Transportation website, etc.

Socioeconomic factors:

- Population density, race and ethnicity, income, education, etc.
- Fairness perspective, are there any potential discrimination?
- Data sources: American Community Survey (ACS), Census, etc.

Accessibility: Spatial econometrics

Classical econometrics with OLS not woking:

$$y = \beta\mathbf{X} + \epsilon, \epsilon \sim \mathbb{N}(0, \sigma^2)$$

- Significant spatial endogeneity among observations (Moran's *I* test, p<0.001);
- Intuitively, this means that the supply or demand of an area is highly affected by its neighbors;
- This leads to over-estimation of classic econometrics with Ordinary Least Squares (OLS).

Spatial econometrics - Lag model:

$$y = \rho\mathbf{W}y + \beta\mathbf{X} + \epsilon, \epsilon \sim \mathbb{N}(0, \sigma^2)$$

- Spatial endogeneity is captured by spatial matrix W;
- Estimated by Maximum Likelihood (ML);
- There are "spillovers", i.e., the effect on one area will affects an another area;
- There are direct effects and indirect effects, combined as total effects.

Accessibility: Fitting results…

Table 1: Estimated average total effects coefficients of citywide (independent) features for four VFH market (dependent) features from spatial lag models in SF. Note: $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.

	Supply (#/5min)			Demand (#/5min)			Price (multiplier)		Wait Time (seconds)	
Average Total Effects	Uber	Lyft	Taxi	Uber	Lyft	Taxi	Uber	Lyft	Uber	Lyft
Constant	**3.1019****	**1.8456****	1.8975	−0.1031	0.1492	−0.1745	**1.0228*****	**1.0771*****	**2.2396****	**1.4378***
Spatial Weight	**0.0727*****	**0.0878*****	**0.0643*****	**0.0509*****	**0.0645*****	**0.0585*****	**0.002***	0.0006	−0.0064	0.0005
Population Density (#/m^2)	−12.4385	−17.98	**60.9386***	−8.9152	**−4.5352***	2.8619	**1.3017*****	−0.8465	**−41.3405*****	**−27.9079****
Public Transit Stops (#)	**0.0361***	0.0135	**0.0472***	**0.0181*****	**0.0039****	**0.0061*****	**−0.0007****	**−0.0018*****	**0.0274*****	**0.0251*****
On-Street Parking Meters (#)	**0.0136*****	**0.0047*****	**0.0085*****	**0.0066*****	**0.002*****	**0.0013*****	**0.0001*****	**0.0001****	**−0.0013*****	**−0.0009****
Off-Street Parking Lots (#)	**0.2053*****	**0.0818*****	**0.3268*****	**0.0744*****	**0.0248*****	**0.0227*****	−0.0	0.0006	**−0.0207***	**−0.0198***
White Number (hundreds)	**0.05***	**0.0283***	**0.1104*****	**0.0266*****	**0.0112*****	[illegible]	0.0	0.0011	0.0068	0.0051
Median Income (thousands)	0.0031	0.0021	[illegible]	[illegible]	[illegible]	[illegible]	−0.0	0.0	−0.0031	**−0.0036***
Median Education Level (year)	−0.1118	[illegible]	−0.0032	[illegible]	[illegible]	**0.0159***	[illegible]	0.003	0.0235	0.0306
Family Ratio (%)	**−2.3186*****	[illegible]	**−2.5165***	[illegible]	[illegible]	−0.1211	[illegible]	**−0.1046*****	**1.7422*****	**1.7647*****
R^2	0.8469	0.8012	[illegible]	0.8802	[illegible]	0.7124	0.5576	0.3566	0.515	0.4837
Sample Size	556	556	[illegible]	556	556	556	166	166	166	166

Table 2: Estimated average total effects coefficients of citywide (independent) features for four VFH market (dependent) features from spatial lag models in NYC. Note: $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.

	Supply (#/5min)			Demand (#/5min)			Price (multiplier)		Wait Time (seconds)	
Average Total Effects	Uber	Lyft	Taxi	Uber	Lyft	Taxi	Uber	Lyft	Uber	Lyft
Constant	**1.7557****	**0.8486*****		**0.4218*****	**0.1343*****		**1.0175*****	**1.0245*****	**2.8244*****	**2.883*****
Spatial Weight	**0.108*****	**0.1036*****		**0.0893*****	**0.0933*****		−0.0042	−0.0003	−0.0287	−0.0171
Population Density (#/m^2)	**−7.8304***	**−5.0664*****		**−3.1914*****	**−1.0124*****		0.4845	0.2053	**−12.9185*****	**−16.4425*****
Public Transit Stops (#)	−0.0227	−0.0101		−0.0042	−0.0009		0.002	**−0.0011***	**0.0287***	**0.0301***
On-Street Parking Meters (#)	**0.0421*****	**0.0141*****		**0.0122*****	**0.0032*****		−0.0004	0.0001	**−0.0042***	−0.0035
Off-Street Parking Lots (#)	**0.5518*****	**0.1671*****		**0.184*****	**0.0446*****		0.0051	−0.0007	−0.0197	−0.038
White Number (hundreds)	−0.0083	0.0004		0.0017	0.0005		0.0005	0.0001	**0.0213****	**0.0228****
Median Income (thousands)	**0.007*****	**0.0017****		**0.001****	0.0002		0.0002	−0.0001	−0.0021	**−0.004***
Median Education Level (year)	−0.0457	−0.0218		**−0.0238****	**−0.0067*****		−0.0035	0.0019	−0.0363	−0.0184
Family Ratio (%)	**−1.7693*****	**−0.6729*****		**−0.236*****	**−0.0699*****		0.0147	−0.0145	**1.3459*****	**1.7871*****
R^2	0.811	0.7473		0.7366	0.7373		0.0225	0.0816	0.3608	0.3756
Sample Size	2451	2451		2451	2451		250	250	250	250

Let's go through some interesting results.

Accessibility: Transportation infrastructure

	Supply (#/5min)			Demand (#/5min)		
Average Total Effects	Uber	Lyft	Taxi	Uber	Lyft	Taxi
Constant	3.1019**	1.8456**	1.8975	−0.1031	0.1492	−0.1745
Spatial Weight	0.0727***	0.0878***	0.0643***	0.0509***	0.0645***	0.0585***
Population Density (#/m^2)	−12.4385	−17.98	60.9386*	−8.9152	−4.5352*	2.8619
Public Transit Stops (#)	**0.0361***	0.0135	**0.0472***	**0.0181*****	**0.0039****	**0.0061*****
On-Street Parking Meters (#)	**0.0136*****	**0.0047*****	**0.0085*****	**0.0066*****	**0.002*****	**0.0013*****
Off-Street Parking Lots (#)	**0.2053*****	**0.0818*****	**0.3268*****	**0.0744*****	**0.0248*****	**0.0227*****
White Number (hundreds)	0.05*	0.0283*	−0.1104***	0.0266***	0.0112***	−0.0106***
Median Income (thousands)	0.0031	0.0021	−0.0025	0.0006	0.0002	−0.0005
Median Education Level (year)	−0.1118	−0.0768*	−0.0032	0.0058	−0.0061	0.0159*
Family Ratio (%)	−2.3186***	−1.1234***	−2.5165***	−0.3969*	−0.2072***	−0.1211
R^2	0.8469	0.8012	0.7303	0.8802	0.8747	0.7124
Sample Size	556	556	556	556	556	556

	Supply (#/5min)			Demand (#/5min)		
Average Total Effects	Uber	Lyft	Taxi	Uber	Lyft	Taxi
Constant	1.7557**	0.8486***		0.4218***	0.1343***	
Spatial Weight	0.108***	0.1036***		0.0893***	0.0933***	
Population Density (#/m^2)	−7.8304*	−5.0664***		−3.1914***	−1.0124***	
Public Transit Stops (#)	−0.0227	−0.0101		−0.0042	−0.0009	
On-Street Parking Meters (#)	**0.0421*****	**0.0141*****		**0.0122*****	**0.0032*****	
Off-Street Parking Lots (#)	**0.5518*****	**0.1671*****		**0.184*****	**0.0446*****	
White Number (hundreds)	−0.0083	0.0004		0.0017	0.0005	
Median Income (thousands)	0.007***	0.0017**		0.001**	0.0002	
Median Education Level (year)	−0.0457	−0.0218		−0.0238**	−0.0067***	
Family Ratio (%)	−1.7693***	−0.6729***		−0.236***	−0.0699***	
R^2	0.811	0.7473		0.7366	0.7373	
Sample Size	2451	2451		2451	2451	

Transportation matters.

- Three factors (public transit, on- and off- street parking) in supply and demand for all Uber, Lyft and taxis services are strongly significant (mean p<0.01);

Transportation matters more than population!

- Population is mostly not significant (mean p>0.3) when transportations are included;
- If we remove transportations, population becomes significant (mean p<0.05).

Accessibility: Socioeconomic factors

Average Total Effects	Supply (#/5min) Uber	Supply (#/5min) Lyft	Supply (#/5min) Taxi	Demand (#/5min) Uber	Demand (#/5min) Lyft	Demand (#/5min) Taxi
Constant	3.1019^{**}	1.8456^{**}	1.8975	−0.1031	0.1492	−0.1745
Spatial Weight	0.0727^{***}	0.0878^{***}	0.0643^{***}	0.0509^{***}	0.0645^{***}	0.0585^{***}
Population Density (#/m^2)	−12.4385	−17.98	60.9386^{*}	−8.9152	-4.5352^{*}	2.8619
Public Transit Stops (#)	0.0361^{*}	0.0135	0.0472^{*}	0.0181^{***}	0.0039^{**}	0.0061^{***}
On-Street Parking Meters (#)	0.0136^{***}	0.0047^{***}	0.0085^{***}	0.0066^{***}	0.002^{***}	0.0013^{***}
Off-Street Parking Lots (#)	0.2053^{***}	0.0818^{***}	0.3268^{***}	0.0744^{***}	0.0248^{***}	0.0227^{***}
White Number (hundreds)	0.05^{*}	0.0283^{*}	-0.1104^{***}	0.0266^{***}	0.0112^{***}	-0.0106^{***}
Median Income (thousands)	0.0031	0.0021	−0.0025	0.0006	0.0002	−0.0005
Median Education Level (year)	−0.1118	-0.0768^{*}	−0.0032	0.0058	−0.0061	0.0159^{*}
Family Ratio (%)	-2.3186^{***}	-1.1234^{***}	-2.5165^{***}	-0.3969^{*}	-0.2072^{***}	−0.1211
R^2	0.8469	0.8012	0.7303	0.8802	0.8747	0.7124
Sample Size	556	556	556	556	556	556

Average Total Effects	Supply (#/5min) Uber	Supply (#/5min) Lyft	Supply (#/5min) Taxi	Demand (#/5min) Uber	Demand (#/5min) Lyft	Demand (#/5min) Taxi
Constant	1.7557^{**}	0.8486^{***}		0.4218^{***}	0.1343^{***}	
Spatial Weight	0.108^{***}	0.1036^{***}		0.0893^{***}	0.0933^{***}	
Population Density (#/m^2)	-7.8304^{*}	-5.0664^{***}		-3.1914^{***}	-1.0124^{***}	
Public Transit Stops (#)	−0.0227	−0.0101		−0.0042	−0.0009	
On-Street Parking Meters (#)	0.0421^{***}	0.0141^{***}		0.0122^{***}	0.0032^{***}	
Off-Street Parking Lots (#)	0.5518^{***}	0.1671^{***}		0.184^{***}	0.0446^{***}	
White Number (hundreds)	−0.0083	0.0004		0.0017	0.0005	
Median Income (thousands)	0.007^{***}	0.0017^{**}		0.001^{**}	0.0002	
Median Education Level (year)	−0.0457	−0.0218		-0.0238^{**}	-0.0067^{***}	
Family Ratio (%)	-1.7693^{***}	-0.6729^{***}		-0.236^{***}	-0.0699^{***}	
R^2	0.811	0.7473		0.7366	0.7373	
Sample Size	2451	2451		2451	2451	

Family ratio is the most important socioeconomic factor.

- Family ratio in supply, demand and price for all Uber, Lyft and taxis services are mostly significant (mean $p<0.001$);

There are "residual" correlations for diverse and low income areas.

- In SF, Uber and Lyft supply is significant increasing (mean $p<0.05$) with Caucasian number.
- In NYC, Uber and Lyft supply is significant increasing (mean $p<0.001$) with median income.

Caution: Effect size is small. * More details in our paper.

Takeaways: Time to wake up!

Competition:

- In the ridesharing market, Uber and Lyft are similar in supply and demand, but different in pricing mechanisms; A small percents of drivers work for Uber and Lyft at the same time;
- In VFH market, ridesharing (Uber and Lyft) are different in supply and demand (and price of course) to taxis, which makes them utilized more efficiently than taxis.

Accessibility:

- Ridesharing (Uber and Lyft) and taxis services are all centered at transportation hubs, and areas with low family ratios;
- Ridesharing (Uber and Lyft) shows “residual” correlation with minority and low-income areas, which could cause potential discrimination, but the effect size is small.

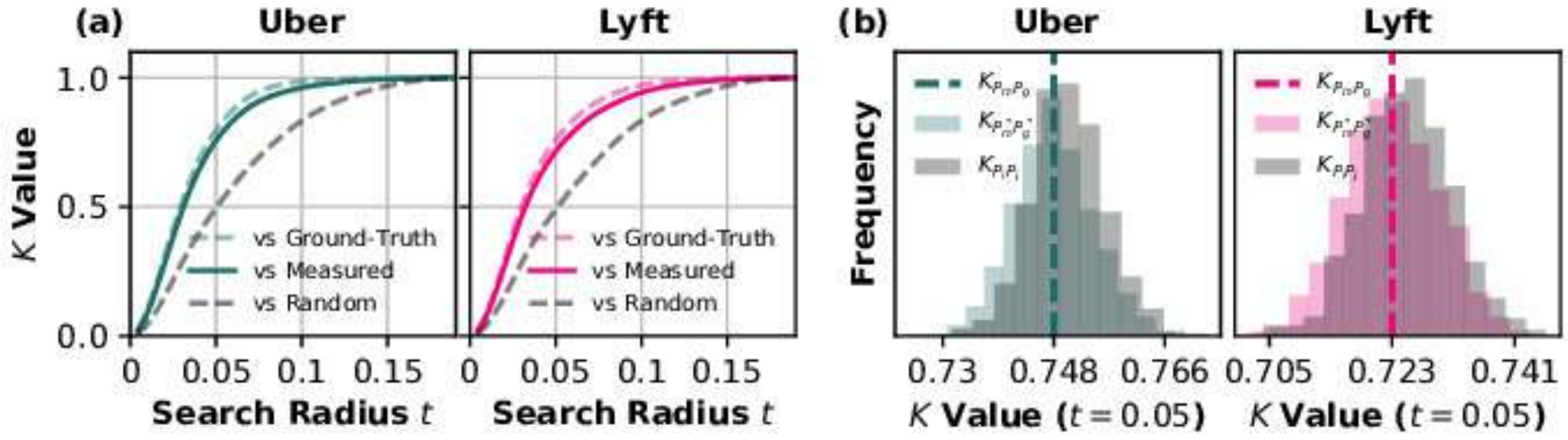
Thanks!

Questions?

Shan Jiang
Email: sjiang@ccs.neu.edu

Northeastern University

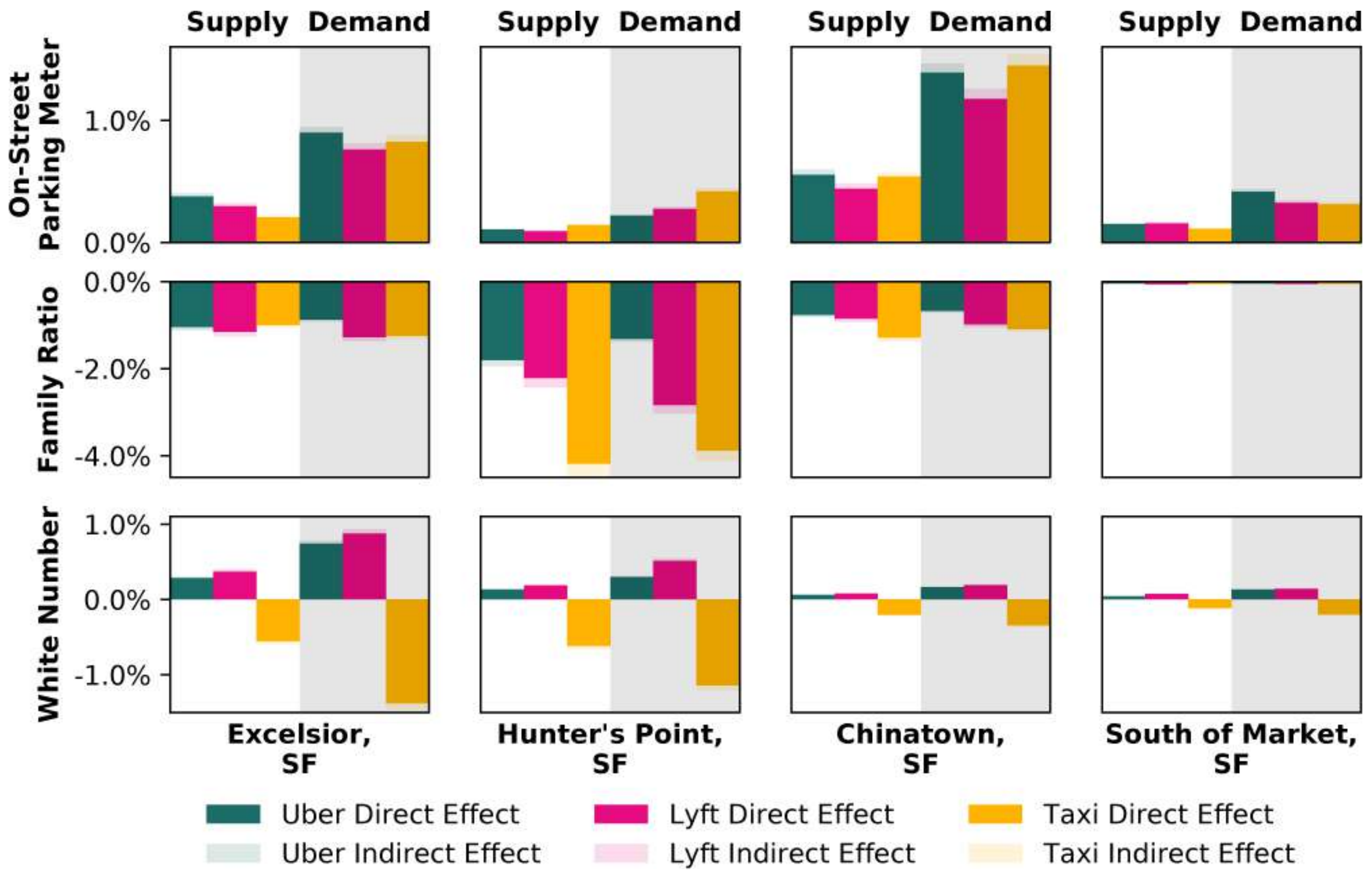
Data validation: Comparison with historical data



Ground truth using a previous opened small Uber dataset in NYC:

- Point pattern statistics: *K* value;
- NO significant different.

Accessibility: Effect size in SF



Accessibility: Effect size in NYC