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

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ABSTRACT

Ridesharing services such as Uber and Lyft have become an important part of the Vehicle For Hire (VFH) market, which used to be dominated by taxis. Unfortunately, ridesharing services are not required to share data like taxi services, which has made it challenging to compare the competitive dynamics of these services, or assess their impact on cities. In this paper, we comprehensively compare Uber, Lyft, and taxis with respect to key market features (supply, demand, price, and wait time) in San Francisco and New York City. Based on point pattern statistics, we develop novel statistical techniques to validate our measurement methods. Using spatial lag models, we investigate the accessibility of VFH services, and find that transportation infrastructure and socio-economic features have substantial effects on VFH market features.

KEYWORDS

ridesharing; vehicle for hire; sharing economy; Uber; Lyft; taxi

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1 INTRODUCTION

Understanding transportation services is essential for a variety of critical tasks, ranging from urban planning and traffic engineering to economic and social mobility. Popular options for urban transportation include private vehicles, public transit, and Vehicle for Hire (VFH) services. Traditionally, the VFH market has been dominated by taxis; however it has recently undergone a dramatic shift due to the rise of the "sharing economy." Today, ridesharing services such as Uber and Lyft augment taxi services in many cities. For example, the Treasurers Office of San Francisco estimates that there are over 45K Uber and Lyft drivers in San Francisco [44], while the San Francisco Municipal Transportation Agency has issued only 2,026 taxi medallions [2]. Similarly, in New York City, Uber and Lyft cars are now estimated to outnumber taxis 4 to 1 [48].

The taxi industry is heavily regulated to promote equitable pricing and access to services, while constraining their impact on infrastructure (e.g., congestion) and the environment. For example, in most cities taxi fare prices are set by law, taxi drivers are required to serve all areas of the city, and the total number of taxis is capped via a licensing regime (e.g., medallions). Furthermore, many cities require that taxi companies periodically report trip-level data to a regulatory agency, to increase transparency and ensure compliance with the law [14]. In contrast, Uber and Lyft both set prices internally (often using opaque algorithms), they are not required to serve all areas of the city, and there are no limits on the total number of ridesharing vehicles. Additionally, ridesharing firms rarely reveal detailed data to regulators [43, 46].

Given the increasing prominence of ridesharing services, and the lack of transparency surrounding their operations, it is crucial to understand how they compare to traditional taxis – and to each other. In this paper, we focus on issues of *competition* and *accessibility*, i.e., do Uber and Lyft offer equal levels of service in terms of *supply* and *price* throughout a given city? Furthermore, do they offer equivalent levels of service to traditional taxis? If not, are there associations between the features of different neighborhoods (e.g., median household incoming, racial/ethic demographics, or access to public transportation) and the observed levels of service? The answers to these questions are critical for urban planners and regulators, as well as to customers of ridesharing services.

In this paper, we take a comprehensive look at the competition and accessibility of Uber, Lyft, and taxis in 2 major U. S. cities. We collect ride-level traces from Uber and Lyft vehicles in San Francisco County (SF) for 40 days, and compare them to corresponding taxi ride traces from the same time period. We also collect and analyze 27 days of Uber and Lyft traces from New York City (NYC). Based on this dataset, we make the following contributions:

- We present the first head-to-head spatial and temporal comparisons of VFH services. This includes a key finding that 1–3% of ridesharing drivers are active on Uber and Lyft simultaneously. In addition, we provide independent validation of key results from prior work on equitability and utilization of ridesharing services [15, 49].
- Based on *point pattern statistics*, we develop a novel Monte Carlo approach for comparing distributions of spatial points. We use this method to validate our observed Uber and Lyft datasets against ground-truth data from NYC [22].
- Using *spatial lag models*, we examine the effects between urban features and VFH service levels, and find that transportation infrastructure (e.g., transit stops) have stronger effects with VFH market features (e.g., supply and demand) than population density, highlighting the interdependence of ridesharing with existing infrastructure. For socio-economic features, we observe that "whiter" neighborhoods in SF and "richer" neighborhoods in NYC have significant effects on supply and demand of ridesharing services, although we caution that the effect sizes are small.

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In the rest of the paper: § 2 presents related work, § 3 describes data collection and validation methods, § 4 presents comparison of VFH services, § 5 examines accessibility, and finally § 6 concludes.

2 RELATED WORK

There is an emerging body of scholarship on ridesharing services. Lee et al. surveyed Uber drivers to understand how they interact with the platform [33], while Guo et al. surveyed passengers to understand why they choose to use ridesharing [26].

Much of the existing literature focuses on the dynamic "surge pricing" systems used by many ridesharing platforms. Uber has been involved in several studies that present positive outcomes from surge pricing, including increased supply of drivers [11, 28], increased consumer surplus [13], and a decrease in "wild goose chase" passenger pickups [8]. In contrast, Chen et al. presented the first independent evaluation of Uber's surge pricing system, and found that it was less effective at increasing driver supply than reducing passenger demand [10]. Guo et al. used data from Didi (the most popular ridesharing service in China) to analyze the relationship between demand and dynamic prices [27], while Kooti et al. used email receipts to examine correlations between passenger demographics and willingness to pay surge prices [32].

Competition with Taxis. Another line of scholarship investigates competition between ridesharing and taxis. Gloss et al. and McGregor et al. studied Uber's impact on the taxi business by interviewing drivers in London and San Francisco [24, 36]. Cramer et al. found that capacity utilization was higher with Uber than taxis, possibly due to Uber's centralized, app-based dispatch system [15]. The different pricing models between Uber and taxis have led researchers to develop price comparison apps to help passengers minimize travel costs [40, 47].

One notable shortcoming of this body of work is that it tends to focus on only Uber, yet ridesharing markets in many countries are oligopolies [37], typically between Uber and Lyft in the U. S. [34].

Accessibility. Several studies have focused on accessibility and discrimination in the gig-economy [19, 30, 49]. Ge et al. found that ridesharing drivers sometimes discriminated against minorities [23], echoing similar studies on taxi drivers [39]. We investigate whether patterns of discrimination are discernible at the level of whole cities.

Thebault-Spieker et al. used a Durbin model to examine how population demographics in Chicago affects wait times for Uber [49]; they found no significant direct effects between income and waiting time. We conduct similar experiments in SF and NYC. However, we view wait times as a proxy for more fundamental market features (i.e., supply, demand, and price) that we focus on in this study. Additionally, case studies on taxi mobility patterns have been conducted in Manhattan, NYC [20] and Shanghai, China [35].

Regulation. The sudden and massive popularity of ridesharing, coupled with the lack of transparency exhibited by ridesharing services, has led to calls for regulation. Calo and Rosenblat argue that information asymmetry gives ridesharing firms a structural advantage against passengers and drivers, and thus they must be regulated [6]. Edelman et al. and Posen et al. discuss potential solutions for regulating Uber [18, 42]. Rogers argues that there may be pro-social benefits if ridesharing services can be properly regulated, although they may simultaneously have a deleterious impact on low-wage workers [45].

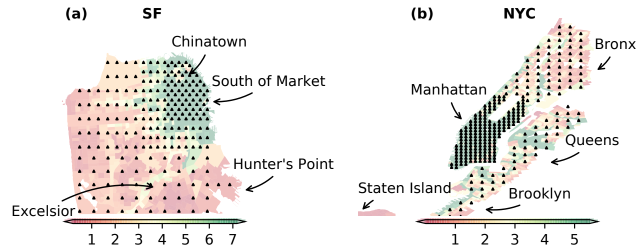

Figure 1: Placement of Uber and Lyft measurement points in (a) SF and (b) NYC. The color represents the average number of ridesharing drivers observed in each block group.

One potential reason to regulate ridesharing services is to compel them to serve all areas of cities equally, as taxis are often required to do. We aim to inform this debate by examining the accessibility of Uber and Lyft vehicles throughout SF and NYC. Although ridesharing companies have shared data publicly in the past [22, 50, 51], these datasets are either high-level aggregated statistics or outdated, and cannot be used to analyze accessibility across VFH service [52]. Therefore, we collected data using the methods described in § 3.

3 DATA

In this section, we present the datasets that we will use throughout this paper. We validate our measured Uber and Lyft datasets using *point pattern statistics* on a small-scale ground-truth dataset released by the NYC Taxi and Limousine Commission (TLC) [22]. Throughout this paper, we focus on UberX and basic Lyft vehicles, since (1) they are the most popular vehicle type offered by these services [10, 32], and (2) they are the most similar to taxis.

3.1 Data Collection

We collected data in SF and NYC, as they are two of the largest markets for ridesharing services [44, 48]. We also chose SF as we were able to partner with the San Francisco County Transportation Authority (SFCTA) to obtain taxi data.

Uber and Lyft. We collected data from Uber and Lyft using their apps [7, 10]. In brief, we recorded the network requests made by Uber and Lyft's smartphone apps for passengers, as well as responses from the servers. To render the onscreen maps with available cars, the apps made requests to the server every five seconds with the user's latitude and longitude; the servers responded with a message that included (1) the GPS coordinates of the eight nearest available cars to the user, (2) the current surge price, and (3) the estimated wait time for a ride at the requested location. The data includes a unique ID for each car, as well as each car's trajectory for the past few seconds.

We created a script that sent the same messages to Uber and Lyft's servers as the passenger apps, and recorded the responses. We can specify the GPS coordinates sent by our script, which gave us the ability to collect data at any location. We collect information for large areas by "blanketing" them with multiple emulated users. We selected the GPS coordinates for each measurement point such that it had a large overlap of the eight nearest cars with the adjacent

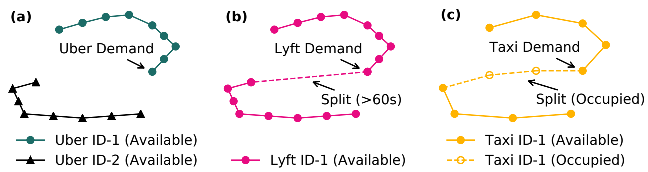

Figure 2: Example car trajectory as it would be observed via (a) Uber, (b) Lyft, and (c) taxi. Each dot represents a GPS coordinate we observe. For Uber and Lyft, we do not observe the cars when they are carrying riders. With Uber, cars are also assigned a new ID each time they pick up a rider.

measurement points, even during rush hour (when the supply of Uber and Lyft cars peaks [10]), so that we did not miss any cars.

The black dots in Figure 1 show the placement of our measurement points for Uber and Lyft. Note that we placed our measurement points more densely in high-traffic portions of each city, to ensure full coverage of cars. In SF, our emulated users covered the entire county; in NYC, we covered all of Manhattan and Staten Island (not shown in Figure 1), the west parts of the Bronx, and the northwest parts of Queens and Brooklyn. We collected data continuously from November 12 to December 22, 2016 in SF, and from February 1 to February 27, 2017 in NYC.

Taxi. The SFCTA provided trip-level taxi records from the greater San Francisco area covering November 1 to December 30, 2016. These records contain, for each taxi: its medallion number, its GPS trace while it is in service, and its occupancy (i.e., when it has a passenger). However, not all taxi companies reported their data to the SFCTA. The dataset contains 554 unique taxi medallions, which represents 27% of the 2,026 medallions that the city has issued [2]. To estimate the entire taxi ecosystem, we assume that the behavior of the missing taxis follow similar distributions to the ones in our dataset. Thus, we estimate taxi supply and demand by multiplying the empirical counts from our dataset by $2026/554 = 3.65$.

Although there is taxi data available from NYC during our measurement interval, it only contains pickup and dropoff points, rather than GPS traces [14]. This limitation precludes us from using the NYC taxi data in this study.

3.2 Data Preprocessing

Next, we discuss how we prepared our Uber, Lyft, and taxi datasets for analysis. Preprocessing is necessary because the information that is available to us from each service is different, and we need to infer market features to understand competition.

Building Trajectories. First, we compute the *trajectories* for each car in our dataset, which are a series of geolocations indexed by time. Figure 2 illustrates the trajectories we can build for cars from each service. For Uber, car IDs in our dataset are transient: each car is assigned a unique ID each time it becomes available to accept a ride request. Therefore, we record vehicle trajectories when the drivers are waiting for ride requests. For Lyft, car IDs in our dataset are persistent, i.e., we observed a unique ID for each vehicle that existed for the entirety of our data collection period; others have also observed this behavior [38]. We split the temporal datastream for a given Lyft vehicle into trajectories by looking for "gaps" of over 60 seconds. During our observation period, more than 99.9% of time gaps for Lyft vehicles were less than 10 seconds, thus we treat large 60 seconds gaps as a signal indicating that a driver accepted a ride request or went offline. For taxis, our dataset contains persistent IDs for drivers and explicit indicators of when each taxi is occupied. Thus, splitting the taxi datastreams into trajectories is trivial.

Inferring Supply, Demand, and Price. Next, we extract three key features that we use to analyze the VFH market: *supply*, *demand*, and *price*. To make our data comparable across VFH services, we discretized all timestamps into a series of five-minute time slots. Furthermore, we group all precise geolocations into *block groups*, which are geostatistical map partitions used by the U. S. Census [9] and the American Community Survey (ACS) [1].

Supply is defined as the total amount of a specific good or service that is available to consumers. We measure supply as *the number of available cars* in a block group at a given time. One potential concern is the case when a driver accepts a ride request and is on their way to pick up the rider. Such a car should not count towards supply. Fortunately, both Uber and Lyft drivers disappear from the set of available cars (and our dataset) once they accept a ride request. Similarly, in our taxi data, taxis that are on their way to pick up a rider are also labeled as being unavailable during this time. Another issue concerns Uber specifically. Uber has an internal tool known as *greyballing* that allows them to send fake data to specific users [31]. In § 3.3, we use statistical tests to determine, with high confidence, that our Uber dataset is not subject to greyballing.

Demand is defined as consumers' desire and willingness to pay a price for a specific good or service. In the VFH context, this means the number of consumers who want to pay for a ride. We are unable to measure this from a passenger's perspective (as we cannot observe users who request rides from Uber and Lyft), but we can infer when a car picks up a rider (as the car will disappear from the set of available cars). We therefore define demand in our context as *the number of fulfilled trips*, and measure it as *the number of disappearing cars* in a block group during a five-minute time slot.

There are several challenges when measuring demand on Uber and Lyft: *first*, when a car disappears, it is possible that the driver logged off, rather than picked up a rider; we expect this case to be infrequent compared to the number of ride requests. However, means that our estimates of demand on Uber and Lyft should be interpreted as upper bounds. *Second*, a car can also disappear from our dataset if it drives outside of our measurement area; we handle this case by detecting cars at the very edge of our measurement area and not counting them as demand [10].

The market price is defined as the current price at which an asset or service can be bought. In the VFH context, we use the average surge price in a block group over the five-minute window as the price for Uber and Lyft. Taxi prices are fixed by law.

3.3 Data Validation

As noted above, there are limitations to our measurement methods, especially when inferring demand. To determine whether our methods are able to accurately capture supply and demand for Uber and Lyft, we validate our dataset against a ground-truth dataset containing the pickup locations (i.e., demand) for Uber and Lyft vehicles in Manhattan from April to September 2014 [22]. The NYC TLC obtained this ground-truth data directly from Uber and Lyft.

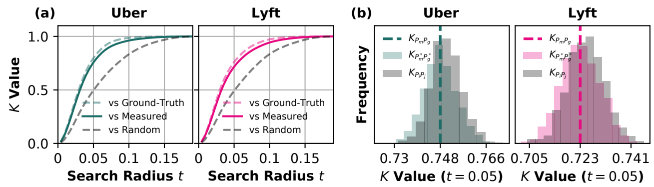

Figure 3: (a) K value for Uber and Lyft as search radius t is varied, and versus randomly sampled points and ground truth. (b) Distribution of K given $t = 0.05$. We observe no statistically significant differences between the measured and ground-truth ridesharing data.

To validate our dataset, we aim to test the null hypothesis:

- H_0: The point patterns P_m and P_g are sampled from the same underlying distribution

where P_m and P_g and the pickup locations for Uber and Lyft rides from our measured and ground-truth samples, respectively. Our high-level approach is to find an appropriate statistical measure to capture the spatial dependency between P_m and P_g, then compare the dependency of P_m and P_g to empirical point patterns drawn from randomized combinations of P_m and P_g.

Spatial Descriptive Statistics. Given two samples of points P_i and P_j, a measure of spatial dependency is the *Bivariate Ripley's K Function* [17], which is defined as:

$$K_{P_iP_j}(t) = \alpha \sum_{i \in P_i} \sum_{j \in P_j} \mathbb{I}(d_{ij} < t), \tag{1}$$

where $\alpha = (\lambda_{P_i} \lambda_{P_j} A)^{-1}$ is a constant, A is the area of the study region, and λ is the density of points; d_{ij} is the Euclidean distance between two points i and j; $\mathbb{I}$ is the indicator function (1 if its operand is true, 0 otherwise); and t is the search radius. Directly computing $K_{P_mP_g}$ is inefficient because of the large size of our datasets. Instead, we estimate $K_{P_mP_g}$ asymptotically using a Monte Carlo approach, i.e., we repeatedly resample P_m^* from P_m and P_g^* from P_g, and compute $K_{P_m^*P_g^*}$. Finally, we can use its expectation $K_{P_mP_g} = \mathbb{E}(K_{P_m^*P_g^*})$. Since we care about the distribution of K rather than its specific value, we set $\alpha = 1$ for simplicity.

The K function counts the number of points from one distribution found within a given search radius of each point of another distribution. Thus, it is used to measure the dependency of two spatial samples. K increases with search radius t; when t is fixed, a larger K represents stronger dependency between the two point patterns. Figure 3 shows the value of K as we vary t for Uber and Lyft; the three lines correspond to P_g compared to P_g, P_m, and a randomly generated point pattern. Intuitively, The dashed lines represent the upper and lower bounds for K. The solid P_g versus P_m lines are very close to the upper bound, thus implying high similarity between the point distributions.

Methods. We adopt a Monte Carlo method to test hypothesis H_0. First, we create the empirical point pattern $P = P_m \cup P_g$, then in each iteration we randomly choose two new samples P_i and P_j from P with $|P_i| = |P_m|$ and $|P_j| = |P_g|$. This relabeling process simulates the point generation process of P_m and P_g. Next, we compute $K_{P_iP_j}$ repeatedly to form an empirical distribution $\mathbb{P}(K_{P_iP_j})$. If P_m and P_g are sampled from P, $K_{P_mP_g}$ can be viewed as a sample drawn from $\mathbb{P}(K_{P_iP_j})$. Conversely, if the underlying distributions of P_m and P_g are significantly different, then $K_{P_mP_g}$ should be outside of the confidence interval of $\mathbb{P}(K_{P_iP_j})$.

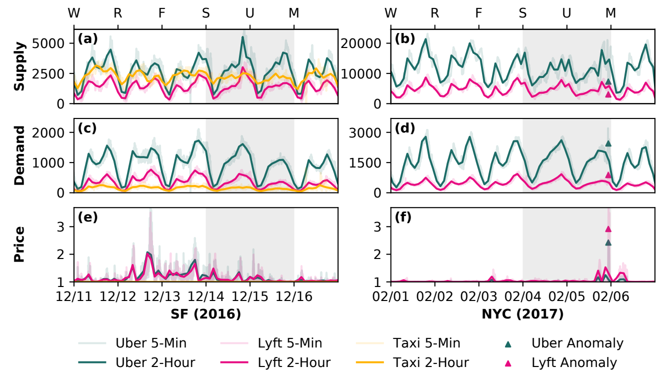

Figure 4: Temporal dynamics of supply, demand, and average surge multiplier in SF and NYC. Data is presented averaged over 5-minute and 2-hour windows. Grey shaded periods are weekends.

Results. The results of our simulations are shown in Figure 3. We ran 2000 iterations with $t = 0.05$ in longitude and latitude scale (note that the choice of t is trivial as long as it does not affect the normality of the distribution). We find no evidence that P_m and P_g are drawn from different distributions ($p = 0.684$ for Uber and $p = 0.744$ for Lyft), thus we cannot reject H_0.

3.4 Ethics

As our methodology collected data from real VFH services, we took careful steps to ensure that our work met ethical standards. First, we did not collect *any* personal information about any Uber, Lyft, or taxi drivers or passengers; all of the identifiers we collect are opaque IDs. Second, we minimized our impact on Uber and Lyft's infrastructure: our script for collecting data had the same behavior as these services' smartphone apps, and did not collect data more aggressively than the app itself would. Third, we never requested rides from Uber or Lyft, and drivers are not able to observe our measurement clients in the driver apps. Thus, our data collection should have no impact on VFH drivers, riders, or services.

4 COMPETITION ANALYSIS

In this section, we focus on the competition between Uber, Lyft and taxis in terms of supply, demand, and price. We examine these services along *temporal* and *spatial* axes.

4.1 Temporal Analysis

To compare the VFH services over time, we aggregate information about supply and demand across all block groups. For price, we compute the average price across all block groups.

Supply and Demand. Figure 4 (a–d) presents the aggregate supply and demand in SF and NYC for each of the three services during a sample of six days from our measurements. We present data averaged over five minute and two hour windows. The anomalies on February 5, 2017 in NYC show a sudden drop in supply and increase in demand, and corresponding increase in price; we hypothesize that these were caused by the Super Bowl.

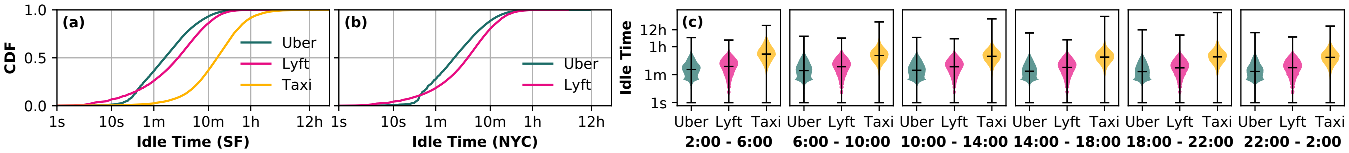

Figure 5: (a–b) Cumulative distribution of the idle time per car across the three services in SF and NYC. (c) Idle time distributions during different times of the day in SF. Note that idle times are presented in log scale. Both overall and throughout the day, taxis show a significantly higher median idle time (>10 minutes) when compared to Uber or Lyft (>1 minute).

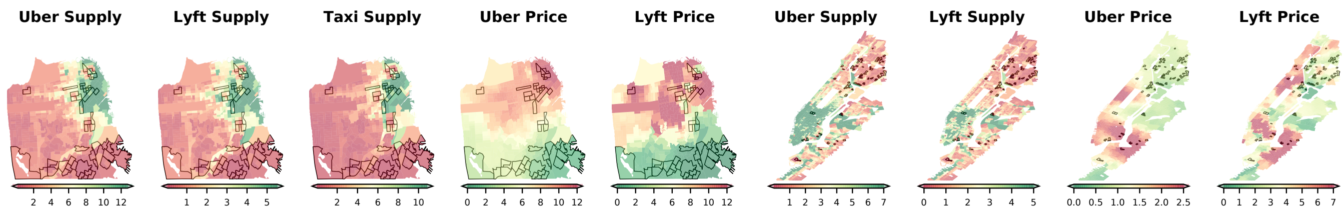

Figure 6: Spatial dynamics of supply and price in SF. The colors capture the average value of each quantity per block group over time. Solid borders indicate Communities of Concern. Demand patterns are very similar to supply, thus we omit them.

We immediately make a number of observations. *First*, we observe similar periodic fluctuations for both supply and demand for Uber and Lyft: on weekdays there are two daily peaks corresponding to morning and evening rush hour. On weekends (shaded grey), there is only one peak per day, typically around noon. On holidays (e.g., Thanksgiving, not shown), there is much lower supply and demand, with no particular peaks. Overall, we observe strong correlation between the supply for Uber and Lyft (Pearson $r = 0.90$ for SF, $r = 0.91$ for NYC, $p < 0.001$) as well as demand (Pearson $r = 0.94$ for SF, $r = 0.92$ for NYC, $p < 0.001$).

Second, we observe that the daily patterns of supply and demand are different for taxis in SF. The supply for taxis maintains a similar pattern every day, and exhibits less variance throughout the day; although there are roughly twice as many Ubers on the road during rush hour, there are often more taxis on the road at night. We attribute these differences between taxis and Uber/Lyft to different employment mechanisms, i.e., Uber/Lyft drivers are considered to be independent contractors and have more freedom to choose when they work. When comparing taxis to Uber and Lyft, we observe relatively weak correlations with supply (Pearson $r = 0.58$ for Uber/Taxi, $r = 0.53$ for Lyft/Taxi, $p < 0.001$) and demand (Pearson $r = 0.62$ for Uber/Taxi, $r = 0.58$ for Lyft/Taxi, $p < 0.001$).

Third, we observe that Uber has 2–2.5× more supply and demand than Lyft. In contrast, the supply of Lyfts and taxis is similar, but the demand for taxis is significantly lower.

Utilization. These findings suggest that taxis spend more time waiting for a rider than Uber and Lyft. To explore differences in utilization, we computed the cumulative distribution of idle time (i.e., how long cars spend waiting for a rider) for each service in Figure 5 (a–b). Uber and Lyft show median idle times of roughly 1 minute, versus roughly 10 minutes for taxis. On average, we found that Lyft drivers spend 19% of their time idling, while taxis spend 48%. These findings hold even when we examine the idle time distributions at different times of the day in SF (Figure 5 (c)). These results provide independent confirmation of those from Cramer et al., who also found (using proprietary data provided by Uber) that Uber vehicles have higher utilization than taxis [15].

Price. We now examine how the citywide average price changes over time. Figure 4 (e–f) shows the average surge price for all three services during one week of our measurements. The taxi price line is always one (as taxi services do not implement surge pricing). Although we see that prices are very noisy for Uber and Lyft, there is strong and significant correlation between these two time series (Pearson $r = 0.82$ for SF, $r = 0.89$ for NYC, $p < 0.001$). This suggests that even though Uber and Lyft's dynamic pricing algorithms may be implemented differently, they both respond similarly to changes in citywide supply and demand, when aggregated temporally.

4.2 Spatial Analysis

Next, we analyze the spatial dynamics of VFH services by calculating the average supply, demand, and price per block group.

Supply and Demand. Figure 6 shows the aggregated supply for Uber, Lyft, and taxi services across SF and NYC, where the color represents the average amount of supply in each block group. We observe that aggregate supply follows a similar geospatial distribution across all three services: most vehicles are available downtown (i.e., near Financial Street in SF and Downtown/Midtown in NYC), and gradually decrease as one moves further from the urban core. Overall, we observed very high similarity across services (Pearson $r > 0.95$ for Uber/Lyft for supply in both cities, and $r > 0.80$ for Ridesharing/Taxi in SF, $p < 0.001$). We observe that demand follows corresponding trends in both cities. Similar results for Uber vehicles have been observed by Chen et al. [10] and Thebault-Spieker et al. [49].

Although we observe similar *aggregate* patterns for supply across the three VFH services, this does not tell us whether *individual car* patterns are the same, i.e., what fraction of the city do individual drivers serve? This is a critical question, since regulated taxi services are required to serve all areas of the city by law, but ridesharing services are not.

To answer this question, we focus on Lyft and taxis in SF (since Lyft car IDs are persistent), and plot the cumulative distribution of the number of unique block groups that each car visits in Figure 7 (b).

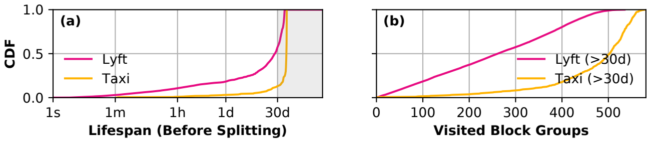

Figure 7: Cumulative distribution of (a) lifespan and (b) number of visited block groups per vehicle.

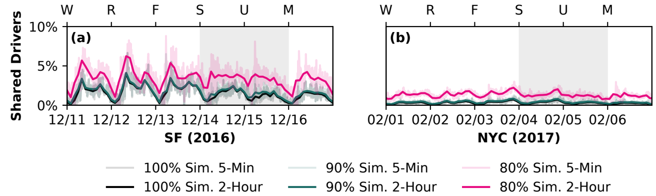

Figure 8: Percentage of shared drivers between Uber and Lyft in (a) SF and (b) NYC over 5-minute and 2-hour windows. Data is presented under 3 different similarity thresholds.

To make the comparison fair, we only examine the 45% of Lyfts and 87% of taxis that we are able to observe for ≥30 days (see Figure 7 (a)). These "full-time" drivers should have ample time over the course of 30 days to drive through the majority of the city.

As shown in Figure 7 (b), the median number of visited block groups for full-time Lyft cars is 261, versus 503 for taxis. There are 580 block groups in SF, meaning each taxi tends to service the whole city, while the majority of Lyft vehicles serve less than half of the city. However, we caution that this result should not be interpreted to mean that Lyft as a whole does not serve all of SF. One possible interpretation of this observation is that Lyft's centralized, computerized dispatch system enables their fleet to more efficiently service the whole city than taxis, even though individual Lyft drivers have small coverage areas. We explore this topic in more detail in § 5.

Price. Finally, we examine the average price for each block group as shown in Figure 6. We observe some similarity between Uber and Lyft: for example, both show the highest prices in the northeastern region and the lowest pricing in the southwestern region in SF. However, the correlation between Uber and Lyft's prices (Pearson $r = 0.67$ for SF and $r = 0.57$ for NYC, $p < 0.001$) is weaker than for supply and demand.

We do observe a number of distinctions between Uber and Lyft's pricing. *First*, Uber seems to surge prices relatively gradually over large areas, while Lyft generates higher prices in very specific neighborhoods, such as South of Market, the Castro, Haight-Ashbury, and Laguna Honda Hospital in SF. These results suggest that Uber and Lyft's algorithms use different approaches to calculate spatial surge prices. We also note that Uber's algorithm has changed significantly since Chen et al. examined it in 2015 [10]. *Second*, Lyft has higher median/peak surges on average (1.08/1.23, s.d. 0.056 in SF; 1.04/1.14, s.d. 0.025 in NYC) than Uber (1.07/1.12, s.d. 0.029 in SF; 1.02/1.03, s.d. 0.007 in NYC).

4.3 Shared Drivers

Prior work has presented anecdotal evidence that some drivers are active on Uber and Lyft simultaneously [24], even though both companies forbid this [21]. However, no one has attempted to quantify the number of "shared" drivers. Identifying such drivers is important, since they are effectively being double-counted in the VFH supply, and therefore helps us to understand the competition between Uber and Lyft.

We identify shared drivers by comparing vehicle trajectories across our three services. Intuitively, if a driver is available on Uber and Lyft simultaneously (e.g., by running their driver apps concurrently, or by using two smartphones), we will observe an Uber and a Lyft vehicle with temporally and spatially coincident trajectories[1]. Furthermore, when a shared driver accepts a request from one service, they will need to immediately log-out of the other service, lest they receive another ride request.

Methods. To identify coincident Uber and Lyft vehicle trajectories, we use the following procedure. We convert the GPS coordinates in each trajectory to block groups and timestamps to 5-minute windows, to deal with the inherent inaccuracies of GPS reports. Now that we have a sequence of time-associated block groups $B = (t_1, b_1) \rightarrow \cdots \rightarrow (t_{|B|}, b_{|B|})$ that a car went though, let B_l and B_u be the trajectories of a given Lyft and Uber car, respectively. We detect shared drivers by calculating the Longest Common Subsequence B_{LCS} between B_l and B_u, while noting that the subsequence is not required to occupy consecutive positions in the block group sequence, since occasionally there are outliers in reported GPS coordinates that map to incorrect block groups. We consider B_l and B_u to be the same driver if $|B_{LCS}| \geq \epsilon \times \min\{c, |B_l|, |B_u|\}$, where ϵ determines the required similarity threshold, and c bounds the minimum block groups required in the sequences so as to avoid trivial matches.

Results. We calculate overlapping trajectories every 5 minutes with $c = 2$ and 3 thresholds 100%, 90%, and 80% for ϵ. Figure 8 presents the percentage of shared drivers over all Uber and Lyft drivers in each window. Under $\epsilon = 100\%$ (i.e., complete trajectory overlap), there are on average around 1.53% shared drivers between Lyft and Uber in SF (0/6.66%, s.d. 0.98%), and 0.32% in NYC (0/1.14%, s.d. 0.19%). This should be viewed as a conservative lower bound on the fraction of shared drivers. When relaxing the threshold to $\epsilon = 80\%$, the percentage increased to average 3.39% in SF (0/8.81%, s.d. 1.42%) and 1.32% in NYC (0/3.01%, s.d. 0.39%). Using the same methods, we find only 0.17% of shared drivers between taxis and ridesharing cars in SF. Given the prior knowledge that taxi drivers cannot work for ridesharing companies, this suggests that the margin of error in our analysis is small.

5 EXPLORING ACCESSIBILITY

In this section we address the question: *are VFH services equally accessible throughout cities?* As shown in Figure 6, the supply and price for VFH services are heterogeneous across block groups; we observe that demand is equally heterogeneous. To better understand this heterogeneity, we fit models using the characteristics of the VFH services as dependent variables, and citywide features as independent variables, including:

[1]We only detect drivers who are active on both services simultaneously, not drivers who are registered for both but only active on a single service at a time.

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*****	**−0.0106*****	0.0	0.0011	0.0068	0.0051
Median Income (thousands)	0.0031	0.0021	−0.0025	0.0006	0.0002	−0.0005	−0.0	0.0	−0.0031	**−0.0036***
Median Education Level (year)	−0.1118	**−0.0768***	−0.0032	0.0058	−0.0061	**0.0159***	**0.0037****	0.003	0.0235	0.0306
Family Ratio (%)	**−2.3186*****	**−1.1234*****	**−2.5165*****	**−0.3969***	**−0.2072*****	−0.1211	**−0.046*****	**−0.1046*****	**1.7422*****	**1.7647*****
R^2	0.8469	0.8012	0.7303	0.8802	0.8747	0.7124	0.5576	0.3566	0.515	0.4837
Sample Size	556	556	556	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****	**0.8846*****		**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

- Transportation infrastructure features, e.g., public transit stops, on-street parking meters, off-street parking lots, etc.
- Socio-economic features, e.g., population density, ethnicity, income, education, etc.

The former set of features are important from a civil engineering perspective: we seek to understand how VFH services interact with the existing transportation infrastructure in cities. The second set of features are important for equitability: by law, taxis must often serve all areas of cities, while no such requirements apply to Uber and Lyft. This raises the possibility that ridesharing services may exhibit discriminatory service patterns.

5.1 Spatial Lag Model

Our first task is selecting an appropriate model for our VFH data. We have found significant spatial autocorrelation between block groups for both supply and demand in SF and NYC (Moran's I test, $p < 0.001$). Such endogeneity makes Ordinary Least Squares (OLS) linear regression inappropriate because the estimated coefficients would overstate the real effects due to the spatial endogeneity.

Instead, we adopt a *spatial lag model* that takes spatial dependencies into consideration [3]. The model is specified as:

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

where y is a market features (supply, demand, price, or wait time), $\mathbf{X} = (1, X_1, X_2, \dots)$ are citywide features of interest (note that we add a constant in the vector), and β is the coefficient vector. $\mathbf{W}y$ is the endogenous term, and its coefficient ρ explains the effect size of spatial dependency. This model is generally estimated by Maximum Likelihood (ML) methods.

Unlike linear regression without endogeneity, the coefficient β in a spatial model is not directly interpretable because spatial endogeneity generates spillovers, i.e., the changes in an independent variable anywhere will affect the value of the dependent variable everywhere [25]. Instead, there are two kinds of related effects associated with independent variables:

- *Direct effects* capture the impact of an independent variable in a specific location on the dependent variable in that same location.
- *Indirect effects* capture the impact of an independent variable in a specific location on the dependent variable in all other locations.

For example, we can estimate the direct effect that median income in a block group has on supply in that block group, as well as the indirect effect that it has on supply in all other block groups. Summing these effects gives us the *total effect* for an independent variable in a given location. Furthermore, since each block group has its own direct and indirect effects, it is often necessary in practice to present *average effects* over the whole study area.

Independent Variables. We gather data for the independent variables in our models from several sources. For socio-economic data, we rely on the ACS [1]. For transportation infrastructure data, we rely on the SF Open Data Platform [16] and the New York City Department of Transportation [41]. We aggregated data into block groups to match the geospatial granularity of our VFH data.

Model Fitting. In our experiments, we fit models for supply, demand, and price for Uber and Lyft in SF and NYC, as well as models for supply and demand for taxis in SF. As a direct comparison to Thebault-Spieker et al. [49], we also repeat their experiments for waiting time. The resulting models are shown in Tables 1 and 2. Our supply and demand models are fit to data at the block group-level. Our price and wait time models are fit to the observed values at each measurement point, coupled with socio-economic and transport data from the block group containing each measurement point. The differing granularity of the models explains why they have different sample sizes. Note that even though price and waiting time have weak spatial endogeneity, we still choose the spatial lag model over OLS as a precaution.

During model fitting, we iteratively removed features to reduce the effects of multicollinearity. The final models all have conditional number test $c < 30$, which is considered acceptable [4].

Diagnostics. We evaluate the goodness-of-fit of our models before examining specific coefficients. We observe that all supply and demand models have $R^2 \geq 0.71$, indicating a strong fit. Additionally, the spatial weight terms are significant ($p < 0.001$), which indicates strong spatial dependency. In contrast, the wait time models are not as strongly fit ($R^2 \geq 0.36$) and not spatially dependent. The price models have the weakest fit, especially in NYC ($R^2 \geq 0.36$ in SF, $R^2 \geq 0.02$ in NYC).

5.2 Transportation Infrastructure

We now examine how VFH market features are affected by the number of public transit stops, on-street parking meters, and off-street parking lots per block group.

Supply and Demand. In SF and NYC, we observe highly significant ($p < 0.001$), positive total effects of the number of parking meters and lots on VFH supply/demand. The sizes of the coefficients tend to be the same order of magnitude across Uber, Lyft, and taxi. The number of public transit stops has somewhat significant ($p < 0.05$), positive effects on supply in SF, and highly significant ($p < 0.01$), positive effects on demand in SF. However, public transit stops do not have a significant effect in NYC. Overall, a 1% increase in off-street parking increases the expected number of Ubers, Lyfts, and taxis by 0.12%, 0.1%, and 0.28% in SF, and the number of Ubers and Lyfts by 0.07% and 0.06% in NYC.

To make these findings concrete, we plot the *individual effect* sizes of the off-street parking feature on supply and demand in Figures 9 and 10 for SF and NYC. The dark bars show the direct effects on the given area, while the light bars show the indirect effects on the rest of the city. We focus on four Communities of Concern (COC) [5] in each city. Bay Area COC are defined by the California Metropolitan Transportation Commission based on eight variables drawn from ACS data, including poverty levels, ethnicity, etc. We used the same thresholds to identify COC around NYC. To make the effect sizes comparable across features with different units, we present *elasticities* when analyzing individual effects, i.e., the percent changes of dependent variables due to a 1% change in an independent variables.

We draw three observations from Figures 9 and 10. First, as expected, the direct effect is always much larger than the indirect effect. Second, the effect size in terms of elasticities is larger in areas with fewer parking meters (e.g., Chinatown versus South of Market). Third, although the effect sizes vary by area, in all cases we see that demand increases more than supply.

Taken together, these results highlight the interdependence of transportation infrastructure and VFH services. We hypothesize that parking meters and (costly) off-street parking lots encourage people to opt for VFH services rather than using their own vehicles. With respect to transit stops in SF, it is unclear why more stops corresponds to more supply and demand. One possibility is that VFH services are being used for "last-mile" services, e.g., getting commuters from transit hubs to their homes. Alternatively, it is possible that people are eschewing public transit options that are perceived as inconvient for more convenient VFH services. This latter hypothesis is supported by surveys of riders [12, 29].

Price and Wait Time. Tables 1 and 2 show that transportation infrastructure features have essentially no effects on surge prices, but some effects on wait times. In SF, although some of the price coefficients are significant ($p < 0.01$), their magnitude is extremely small, meaning there is little impact in practice. Wait times in SF and NYC are significant ($p < 0.05$) and positive with respect to public transit stops, but significant ($p < 0.05$ in SF) and negative with respect to parking features. Our wait time results match those from prior work on Uber [49].

Population Density. One important question is whether population density explains the association we observe between VFH market features and transportation infrastructure. For example, we would expect there to be more transit stops in highly populated areas, which might also correspond to a large demand for VFH services. However, our models include population density, and we see that it has mixed effects on VFH market features (sometimes positive, sometimes negative). Furthermore, we find that population density is negatively affected by transportation infrastructure features (e.g., Pearsons $r = -0.28$ for public transit stops and $r = -0.16$ for off-street parking lots, $p < 0.001$, in SF). Thus, we conclude that transportation infrastructure does have strong and distinct effects on VFH market dynamics, independent of population density.

5.3 Urban Socio-Economics

Next, we examine the effect of urban socio-economics on VFH market features.

Family Ratio. The family ratio is the fraction households in a block group containing families [1]. Since this feature is not sensitive, we examine it first and treat it as a baseline when discussing more sensitive socio-economic features.

As shown in Tables 1 and 2, the family ratio has highly significant ($p < 0.001$) effects on almost all VFH market features across all three services in both cities. As the family ratio increases, supply and demand decrease, while wait times increase, and in SF prices increase. Figures 9 and 10 show that the effect size for the family ratio can be large: for example, in Hunter's Point and Red Hook, an increase in the number of families by 1% would reduce supply and demand by 1–8%. We hypothesize that the strong effects of the number of families on VFH market features are caused by (1)

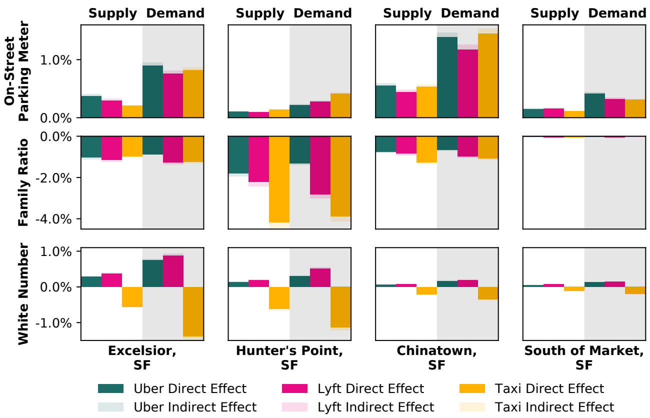

Figure 9: Direct and indirect effect sizes of three citywide features on supply and demand in four COC in SF.

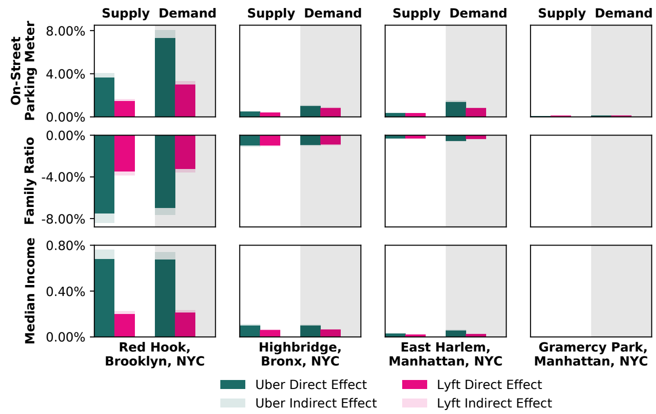

Figure 10: Direct and indirect effect sizes of three citywide features on supply and demand in four COC in NYC.

the need for families to own private cars and (2) the prevalence of families in the suburban periphery of cities.

Ethnicity in SF. Next we examine ethnicity, which we encode as the number of individuals who self-identify as white or caucasian per block group. We do not observe significant effects in NYC, but do in SF. Specifically, we observe significant ($p < 0.05$), positive effects of the number of white individuals on supply/demand for Ubers and Lyfts, but significant ($p < 0.001$), negative effects on supply/demand for taxis. While these effects are troubling and consistent across block groups in SF (see Figure 9), we caution that the effect size is small: as shown in Figure 9, even in areas of SF with large minority populations like Excelsior and Hunter's Point, a 1% increase in the number of white residents would only increase supply/demand for ridesharing by <1%. Contrast this to the much larger effect sizes for changes in the family ratio. Furthermore, Table 1 shows that the number of white individuals does not significantly affect price or wait time in SF (or NYC), so we cannot conclude that minority areas of SF are being substantively disadvantaged by the lower supply of ridesharing vehicles.

It is unclear why the fraction of white residents in SF has different effects on ridesharing and taxi ridership. One possibility is that systematic discrimination by ridesharing drivers that has been observed by prior audits studies [23] has trained ethnic minority passengers to rely on taxis instead. However, this hypothesis belies similar, well-documented discrimination by taxi drivers [39]. Another possible explanation is that because the law stipulates that taxis must serve all areas of the city, taxi drivers have been trained to visit more diverse areas than ridesharing drivers. Given that there is a small positive correlation between the number of white residents per block group and transportation infrastructure in SF (Pearson $r = 0.15$ for public transit stops, $p < 0.001$), the negative coefficient may essentially be compensation for less transportation infrastructure in minority communities.

Income in NYC. Finally, we examine the effects of median income on VFH market features. We do not observe significant effects in SF, but do observe significant ($p < 0.01$), positive effects on supply in NYC. However, similar to ethnicity, the sizes of the "wealth" effect are small: Figure 10 shows that a 1% increase in median income only increases supply and demand for ridesharing by <1%, although this effect is consistent across block groups. We do not observe significant effects of median income on price in NYC, and only weak effects on wait times. Note that there is weak, positive correlation between ethnicity and median income (Pearson $r = 0.27$ for SF and $r = 0.47$ for NYC, $p < 0.001$), therefore it is expected to see some mixed effects of these features.

6 DISCUSSION

Urban transportation services serve a critically important role in our society, and a proper understanding of their dynamics is essential for a variety of tasks. Recently, ridesharing has begun to "disrupt" long-standing services such as taxis and public transportation. However, despite their popularity, we know relatively little about the service that incumbent ridesharing services provide, and how they interact with existing services and the city as a whole.

In this paper, we present the first head-to-head comparison of Uber, Lyft, and taxis. We collect 40 days of data in SF and 27 days in NYC from Uber and Lyft's mobile applications, and obtained taxi data in the same time period from the SFCTA. From this data, we extracted four key market features from all three services: price, supply, demand, and wait time.

Our results extend the existing VFH literature in key ways. First, we introduce a novel statistical method for validating measured ridesharing data. Second, we highlight key differences between Uber and Lyft's surge pricing algorithms (and update findings from prior work [10]), and show that a significant fraction of Lyft drivers are simultaneously driving for Uber as well. Third, we rigorously investigate the accessibility of VFH services across SF and NYC using spatial lag models. Overall, our results independently confirm key findings from the economics literature [15], and provide a quantitative complement to qualitative survey results about the equitability of ridesharing [23].

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REFERENCES

[1] ACS. 2015. American Community Survey. (2015). http://www.census.gov/programs-surveys/acs.

[2] San Francisco Municipal Transportation Agency. 2016. Taxi Medallion by Company Statistics. (6 2016). http://www.sfmta.com/services/taxi-industry/medallions/medallion-holders.

[3] Luc Anselin. 2001. Spatial econometrics. *A companion to theoretical econometrics* 310330 (2001).

[4] David A Belsley. 1991. *Conditioning diagnostics: Collinearity and weak data in regression*. Number 519.536 B452. Wiley.

[5] California, Metropolitan Transportation Commission 2012. Communities of Concern, San Francisco Bay Area, California 2005-2009. (2012). http://purl.stanford.edu/dp294hh9321.

[6] Ryan Calo and Alex Rosenblat. 2017. The Taking Economy: Uber, Information, and Power. *Columbia Law Review* 117 (March 2017).

[7] Joe Castiglione, Tilly Chang, Drew Cooper, Jeff Hobson, Warren Logan, Eric Young, Billy Charlton, Christo Wilson, Alan Mislove, Le Chen, and Shan Jiang. 2016. TNCs Today: A Profile of San Francisco Transportation Network Company Activity. *San Francisco County Transportation Authority* (June 2016).

[8] Juan Camilo Castillo, Daniel T. Knoepfle, and E. Glen Weyl. 2017. Surge Pricing Solves the Wild Goose Chase. SSRN. (July 2017).

[9] Census. 2010. Census Block Groups. (2010). https://www.census.gov/geo/reference/gtc/gtc_bg.html.

[10] Le Chen, Alan Mislove, and Christo Wilson. 2015. Peeking Beneath the Hood of Uber. In *Proc. of IMC*.

[11] M Keith Chen and Michael Sheldon. 2015. *Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform*. Technical Report. UCLA.

[12] Regina R. Clewlow and Gouri Shankar Mishra. 2017. *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. Technical Report. UC Davis, Report UCD-ITS-RR-17-07.

[13] Peter Cohen, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. 2016. *Using big data to estimate consumer surplus: The case of uber*. Technical Report. NBER.

[14] NYC Taxi & Limousine Commission. 2017. TLD Trip Record Data. (2017). http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml.

[15] Judd Cramer and Alan B. Krueger. 2016. Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review* 106, 5 (2016), 177–182.

[16] San Francisco Open Data. 2012. SF Public Transportation Data. (3 2012). http://data.sfgov.org/Transportation/SFMTA-routes-and-stops-for-March-2012/f5c3-8kkj.

[17] Philip M Dixon. 2002. Ripley's K function. *Encyclopedia of environmetrics* (2002).

[18] Benjamin G Edelman and Damien Geradin. 2015. Efficiencies and regulatory shortcuts: How should we regulate companies like Airbnb and Uber. *Stan. Tech. L. Rev.* 19 (2015), 293.

[19] Benjamin G Edelman and Michael Luca. 2014. Digital discrimination: The case of Airbnb.com. (2014).

[20] Lisette Espin Noboa, Florian Lemmerich, Philipp Singer, and Markus Strohmaier. 2016. Discovering and Characterizing Mobility Patterns in Urban Spaces: A Study of Manhattan Taxi Data. In *Proceedings of the 25th International Conference Companion on World Wide Web (WWW '16 Companion)*. 537–542.

[21] Erica Fink. 2014. Uber threatens drivers: Do not work for Lyft. CNN. (8 2014). http://money.cnn.com/2014/08/04/technology/uber-lyft/index.html.

[22] FiveThirtyEight. 2015. Uber Pickups in New York City. Kaggle. (9 2015). https://www.kaggle.com/fivethirtyeight/uber-pickups-in-new-york-city.

[23] Yanbo Ge, Christopher R Knittel, Don MacKenzie, and Stephen Zoepf. 2016. *Racial and gender discrimination in transportation network companies*. Technical Report. NBER.

[24] Mareike Glöss, Moira McGregor, and Barry Brown. 2016. Designing for labour: uber and the on-demand mobile workforce. In *Proc. of CHI*.

[25] André Braz Golgher and Paul R Voss. 2016. How to interpret the coefficients of spatial models: Spillovers, direct and indirect effects. *Spatial Demography* 4, 3 (2016), 175–205.

[26] Suiming Guo, Yaxiao Liu, Ke Xu, and Dah Ming Chiu. 2017. Understanding passenger reaction to dynamic prices in ride-on-demand service. In *Proc. of PerCom Workshops*.

[27] Suiming Guo, Yaxiao Liu, Ke Xu, and Dah Ming Chiu. 2017. Understanding ride-on-demand service: Demand and dynamic pricing. In *Proc. of PerCom Workshops*.

[28] Jonathan V Hall and Alan B Krueger. 2016. *An analysis of the labor market for Uber's driver-partners in the United States*. Technical Report. NBER.

[29] Robert Cornelius Hampshire, Chris Simek, Tayo Fabusuyi, Xuan Di, and Xi Chen. 2017. Measuring the Impact of an Unanticipated Suspension of Ride-Sourcing in Austin, Texas. SSRN. (May 2017).

[30] Aniko Hannak, Claudia Wagner, David Garcia, Alan Mislove, Markus Strohmaier, and Christo Wilson. 2017. Bias in Online Freelance Marketplaces: Evidence from TaskRabbit and Fiverr. In *Proc. of CSCW*.

[31] Mike Issac. 2017. How Uber Deceives the Authorities Worldwide. New York Times. (3 2017). http://nyti.ms/2mBwTH0.

[32] Farshad Kooti, Mihajlo Grbovic, Luca Maria Aiello, Nemanja Djuric, Vladan Radosavljevic, and Kristina Lerman. 2017. Analyzing Uber's Ride-sharing Economy. In *Proc. of WWW Companion*.

[33] Min Kyung Lee, Daniel Kusbit, Evan Metsky, and Laura Dabbish. 2015. Working with machines: The impact of algorithmic and data-driven management on human workers. In *Proc. of CHI*.

[34] Michal Lev-Ram. 2017. How Lyft Could Defeat Uber. Fortune. (7 2017). http://fortune.com/2017/07/19/uber-vs-lyft-race/.

[35] Xi Liu, Li Gong, Yongxi Gong, and Yu Liu. 2015. Revealing travel patterns and city structure with taxi trip data. *Journal of Transport Geography* 43 (2015), 78 – 90.

[36] Moira McGregor, Barry Brown, and Mareike Glöss. 2015. Disrupting the cab: Uber, ridesharing and the taxi industry. *Journal of Peer Production* 6 (2015).

[37] Jared Meyer. 2016. Uber Is Not (And Will Never Be) A Monopoly. Forbes. (2 2016). https://www.forbes.com/sites/jaredmeyer/2016/02/15/uber-guardian-not-monopoly-ridesharing.

[38] Mariella Moon. 2017. Uber's 'Hell' program tracked and targeted Lyft drivers. Engadget. (4 2017). http://engt.co/2oBME0K.

[39] Benjamin Mueller. 2016. $25,000 Fine Proposed in Taxi Driver's Snub of Black Family. New York Times. (8 2016). http://nyti.ms/2yy4WVm.

[40] Anastasios Noulas, Vsevolod Salnikov, Desislava Hristova, Cecilia Mascolo, and Renaud Lambiotte. 2017. Developing and Deploying a Taxi Price Comparison Mobile App in the Wild: Insights and Challenges. *arXiv preprint arXiv:1701.04208* (2017).

[41] New York City Department of Transportation. 2014. NYC Public Transportation Data. (9 2014). http://www.nyc.gov/html/dot/html/home/home.shtml.

[42] Hannah A Posen. 2015. Ridesharing in the Sharing Economy: Should Regulators Impose Uber Regulations on Uber. *Iowa L. Rev.* 101 (2015), 405.

[43] Associated Press. 2016. Boston wants better data from Uber, and is taking a roundabout route to try and get it. Boston Globe. (6 2016). https://www.boston.com/news/business/2016/06/28/uber-data-boston-wants.

[44] Joe Fitzgerald Rodriguez. 2016. 45,000 Uber and Lyft drivers may now operate in SF. SF Examiner. (11 2016). http://bit.ly/2gtgRsj.

[45] Brishen Rogers. 2015. The social costs of Uber. *U. Chi. L. Rev. Dialogue* 82 (2015), 85.

[46] Carolyn Said. 2017. SF demands data from Uber, Lyft on city trips, driver bonuses. San Francisco Chronicle. (6 2017). http://www.sfchronicle.com/business/article/SF-goes-after-Uber-Lyft-for-data-on-city-trips-11196961.php.

[47] Vsevolod Salnikov, Renaud Lambiotte, Anastasios Noulas, and Cecilia Mascolo. 2015. OpenStreetCab: exploiting taxi mobility patterns in New York City to reduce commuter costs. *arXiv preprint arXiv:1503.03021* (2015).

[48] Rachel Sugar. 2017. Uber and Lyft Cars Now Outnumber Yellow Cabs in NYC 4 to 1. Curbed. (1 2017). http://ny.curbed.com/2017/1/17/14296892/yellow-taxi-nyc-uber-lyft-vianumbers.

[49] Jacob Thebault-Spieker, Loren Terveen, and Brent Hecht. 2017. Toward a Geographic Understanding of the Sharing Economy: Systemic Biases in UberX and TaskRabbit. *ACM Trans. Comput.-Hum. Interact.* 24, 3 (April 2017), 21:1–21:40.

[50] Uber. 2017. Uber Movement. (2017). https://movement.uber.com.

[51] Adam Vaccaro. 2015. Uber to Hand Over Trip Data to Boston. Boston. (1 2015). https://www.boston.com/news/technology/2015/01/13/uber-to-hand-over-trip-data-to-boston.

[52] Adam Vaccaro. 2016. Highly Touted Boston-Uber Partnership Has Not Lived Up to Hype So Far. Boston. (6 2016). https://www.boston.com/news/business/2016/06/16/bostons-uber-partnership-has-not-lived-up-to-promise.