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Impacts of trip characteristics and weather condition on ride-sourcing network: Evidence from Uber and Lyft

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ABSTRACT

This paper evaluates the impact of intracity routes and weather conditions on pick-up waiting time, trip duration, and ride fare with a focus on the ride-sourcing mode in the city of Philadelphia, in the U.S. For our analysis, ride estimate data has been collected from Uber and Lyft developers' Application Program Interfaces (API), and weather information has been collected from Yahoo weather API during summer 2018. It should be noted that the generated trips for both ride-sourcing services are for solo and pool rides. Time fixed effect ordinary least squares model was adopted in this paper for analysis purposes.

The results show that trips originated from the city center zone have higher fares compared to the trips head toward the city center. Further, it is observed that trips with origins and destinations close to the city center zone have longer trip durations. Our findings confirm that pick-up waiting time, trip duration, and fare increase in extreme weather conditions during weekdays; while they decrease during weekends. In the end, comparing Uber with its main competitor, Lyft, shows that Uber rides are faster than Lyft. However, Lyft rides are cheaper and more accessible compared to Uber in both pool and solo rides.

1. Introduction and background

Information and Communication Technologies (ICT) create new types of value for both companies and customers (Laurell & Sandström, 2016; Pihl, 2014; Pihl & Sandström, 2013). Companies such as Uber, Airbnb, Lyft, e-Bay, Craigslist, and Amazon developed ICT based business models that provide affordable services for customers. These business models provide new levels of scalability that enable companies to serve thousands of customers. Simultaneously, they generate massive amounts of raw data regarding their business with their customers. This data reflects the day to day dynamics of the companies' performance and their customers' buying behavior (e.g. Liu et al., 2017; Weckström et al., 2018). Companies may get benefits from this data to assess their financial and non-financial business operations by employing data-driven methods (e.g. Hensher, 1997; Liu et al., 2017). The output of such analytic methods enables managers to better track and interpret variations in companies' performances and provide solutions to enhance the quality of services (Jiao, 2018; Terrien, Maniak, Chen, & Shaheen, 2016). For instance, ride-sourcing companies use their customer data to better understand their travel behaviors in different situations (i.e. weather conditions), locations and different dates that provide valuable insights helping to enhance their services.

Uber and Lyft are the examples of ride-sourcing companies that use ICT platforms. These companies are known as Transportation Network Companies (TNCs), which simply work through mobile applications that connect individuals (i.e. customers) willing to pay for a ride with independent drivers willing to provide a ride with their privately-owned vehicles. In the concept of ride-sourcing business, these privately-owned vehicles are non-dedicated to providing a transport service to the public. In the ride-sourcing business, riders open a TNC's mobile application and search for the available rides for a specific route. Then, they can choose to request a ride. If a ride request is sent, then the TNC's application calculates the fare according to the time and the distance that will be traveled and bills the rider automatically. In 2016, Uber has been operated in over 503 cities across 77 countries. In the United Kingdom, London alone, more than 1 million Londoners have shared their trips by using Uber services (Rodionova, 2016). These Uber services motivated riders to not use their own vehicles for their daily

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transportation. Therefore, more than 700,000 driving miles and consequently 50,000 L of petrol have been saved that decreased the emission of carbon dioxide by 124 metric tons (Rodionova, 2016). Lyft also operates in 30 U.S. states (Harding, Kandlikar, & Gulati, 2016). In 2017, Uber and Lyft owned 54% and 37% of the United States ride-sourcing market, respectively (Certify, 2017).

The popularity of these companies is mainly due to their convenience, lower cost and faster services in comparison with traditional taxi systems. For instance, Rayle, Shaheen, Chan, Dai, and Cervero (2014) showed that waiting time for the ride-sourcing services in San Francisco is significantly lower than traditional taxi services. Another study claimed that the average price for an Uber trip in Los Angeles was $7.26 compared to $17.09 for an equivalent traditional taxi trip (i.e. 42.48% cheaper) (Smart, Rowe, Hawken, & others, 2015). In terms of convenience, TNCs provide automatic online payment through the mobile applications, which is much more convenient, safer and faster than other payment options (i.e. using cash or debit/credit card) used by traditional taxi systems (Hughes & MacKenzie, 2016). In comparison with other modes of public transportation (buses, subways), there have been a lot of debates regarding the confrontation between ride-sourcing and public transportation services in North America in terms of their convenience, cost fare, traffic and their impacts of environment (Hill, 2018). Riders in big cities often prefer Uber or Lyft services due to their convenience in terms of the availability in different locations and fast services even though their cost fares are higher. This preference has increased the annual rate of using ride-sourcing services (Hill, 2018).

Demand in the ride-sourcing market has a large fluctuation (de Souza Silva, de Andrade, & Alves Maia, 2018; Schwieterman & Smith, 2018; Shokoohyar, 2019). Drivers also have flexibility in deciding whether, when and where to provide services to maximize their expected earnings. This flexibility causes a variable supply of drivers. To improve the quality of ride-sourcing services, and better manage demand fluctuations, TNCs employ fare adaption policies (Zhang, Wen, & Zeng, 2016). A fare adaption policy used by TNCs is a strong tool to equilibrate the demand (riding requests) with the supply (drivers). This policy results in developing dynamic pricing methods to mitigate the impact of temporal demand fluctuations on service and in turn increase the profit at given locations (Jiao, 2018; Ozkan & Ward, 2017). Furthermore, the policy affects non-financial performance of TNCs, such as average pick-up waiting times and average trip durations (Cohen & Zhang, 2017). This influences the preference of customers to use ride-sourcing services versus traditional taxi systems or public transit systems (Jiao, 2018).

Ride-sourcing platforms from supply side have usually been studied from two different perspectives. First perspective considers the dependency of the supply of drivers to fare adaption policies. Hall, Kendrick, and Nosko (2015) investigated the effects of dynamic fare pricing on the average waiting times in high demand locations. They showed that fare adaption policies vary depending on areas of operations, times of the ride, length of the ride, and other factors that are not transparent to outside observers (Cohen & Zhang, 2017; Liu et al., 2017; Ozkan & Ward, 2017; Scheiber, 2017; Schwieterman & Smith, 2018; Shokoohyar, 2018b; Zhang et al., 2016). Employing an adaption fare policy closes the gap between supply and demand. This in turn leads to improve outcomes for both riders (i.e. a reduction in pick-up waiting times) and driver partners (higher earnings). Chen and Sheldon (2016, p. 455) studied the impact of dynamic pricing of trips on drivers' behaviors in a ride-sourcing platform. They showed that drivers adjust their availability in order to drive more at high surge times. Guda and Subramanian (2019) studied how sharing market demand forecast with drivers and using surge pricing can be useful for ride-sourcing platforms to control the supply of drivers in different locations. Few studies also directly investigated the impact of fare adaption polices on drivers' strategies. For instance, Malin and Chandler (2017) interviewed with 18 Pittsburg-based Uber and Lyft drivers. Shokoohyar (2018a) studied the impact of fare adaption policies through analyzing drivers' comments on social networks. These studies confirm the significant impact of fare adaption polices on drivers' supply.

The second perspective considers the relation between supply of drivers in different locations and the corresponding socio-economics factors and transportation infrastructures. Several studies showed that the supply of drivers is higher in denser areas and Uber and Lyft are more accessible in these areas (Hughes & MacKenzie, 2016; Shokoohyar, Sobhani, & Ramezanpour Nargesi, 2020; Sobhani & Wahab, 2017). Shokoohyar et al. (2020) observed that Uber is more accessible in areas with higher transit score in the city of Philadelphia. This result is in line with findings of Wang and Mu (2018). Jiang, Chen, Mislove, and Wilson (2018) investigated the accessibility of Uber services and minority rates in different urban locations. Their findings conclude that there is no significance relationship between them. However, the above perspectives rarely consider the effects of weather conditions on the supply of drivers.

Understanding the effects of weather conditions on human travel behavior is essential for policy makers and traffic managers to get insights regarding changes of travel decisions (Böcker, Dijst, & Prillwitz, 2013; Cools & Creemers, 2013; Cools, Moons, & Wets, 2010; Cramer & Krueger, 2016; Shokoohyar, Qi, & Katok, 2019). Trip cancellation, changes in the destination of traveling, changes in the time of in-city travel, changes in the transport mode are all examples of the potential travel decision modifications that affect traffic and also the demand for different mode of transportations including ride-sourcing services (Cramer & Krueger, 2016; Koetse & Rietveld, 2009; Rayle, Dai, Chan, Cervero, & Shaheen, 2016; Singhal, Kamga, & Yazici, 2014; Sumalee, Uchida, & Lam, 2011). For instance, Rose, Ahmed, Figliozzi, and Jakob (2011) examined the relationship between weather and cycling travel behavior. Their studies revealed that warmer temperatures and less rainfall increase bicycle traffic in cities while heavy rain reduces the bicycle traffic as cyclists prefer to use other modes of transportation. A survey among transit users in Salt Lake City, Utah demonstrated that given 12% of transit riders avoided transit due to unfavorable weather conditions (Outwater et al., 2011). Stover and McCormack (2012) also examined the effects of weather conditions on daily bus ridership. Their findings revealed that adverse weather conditions like high winds, thunderstorms, and heavy rains have a negative impact on using transit ridership. People in these weather situations are usually prefer to use their own vehicles or ride-sourcing services (Cramer & Krueger, 2016). Therefore, the demand for rid-sourcing services increases. Brodeur and Nield study demonstrated a significant correlation between the number of Uber rides and rainy weather in New York City (Brodeur & Nield, 2018).

Similar to weather condition effects, both pick-up and drop-off locations are also factors that might significantly influence the demand in different locations, and consequently, the dynamics of ride fares. Specifically, the effects of all these factors on ride fares, average pick-up times, and/or trip durations are important for customers, and might have an effect on their preferences when requesting a ride-sourcing service from a given TNC company (i.e. using UberPool versus UberX, or using Lyft vs Uber). For instance, Brodeur and Nield (2017) demonstrated that the number of Uber rides increased by around 25% in New York City when it was raining, while the number of taxi rides increased by only 4% during the same rainy hours. These findings suggested that the fare adoption policy used by Uber increases the supply of drivers to cover the high demand of rider requests during rainy weather conditions. They also concluded that it is easier to catch a ride in rainy hours than in non-rainy hours in high demand locations as the fare adoption policy of Uber stimulates riders by increasing riding fares. That being said, to the best of authors' knowledge, previous studies barely explored non-financial performances of TNCs and their fare adoption policies together in relation to weather conditions, origin-destination of trips, and different types of ride-sourcing services (i.e. pool versus solo rides). Additionally, there is no study comparing different ride-sourcing providers in this context. Hence, this is where our study stands.

1.1. Study context

In order to evaluate TNCs fare adaption policies and span the research gap in the literature, this study was twofold: 1) evaluating the effects of weather conditions, origin-destination locations, and types of ride-sourcing on non-financial performance of TNCs (i.e. average pick-up times, and trip durations), and 2) investigating the impact of weather conditions, origin-destination locations, and different types of ride-sourcing (i.e. Solo and Pool) on the ride fare of two major ride-sourcing service providers (i.e. Uber and Lyft). Moreover, findings from the Uber and Lyft data analysis are compared in the paper. The city of Philadelphia, U.S., was selected for a case study as both solo and pool rides are provided by both Uber and Lyft in most areas of the city. The Uber, Lyft and weather conditions data were collected from June 7th to June 20th, in summer 2018 in Philadelphia. This paper contributes to the literature by providing valuable insights into the TNCs by studying how demands react to different weather, and/or market conditions in different locations. For this reason, extensive descriptive and the Ordinary Least Squares (OLS) modeling were employed in the paper. Findings are interpreted from both customers and ride-sourcing service providers' sides.

The reminder of this paper is organized as follows. Section 2 describes the methodologies used to collect and analyze data. Section 3 presents the model results with a focus on trip pick-up waiting time, trip duration, and trip fare in details. Finally, policy implications of the findings, summary of the paper and future research are discussed in Section 4 and 5.

2. Data collection and methodology

In this section, data collection procedure and the employed time fixed effect Ordinary Least Squares model (OLS) for analysis purposes are presented in detail.

2.1. Data collection

Sample data was collected by accessing three Application Program Interfaces (API): Uber, Lyft, and Yahoo weather. Uber's and Lyft's APIs

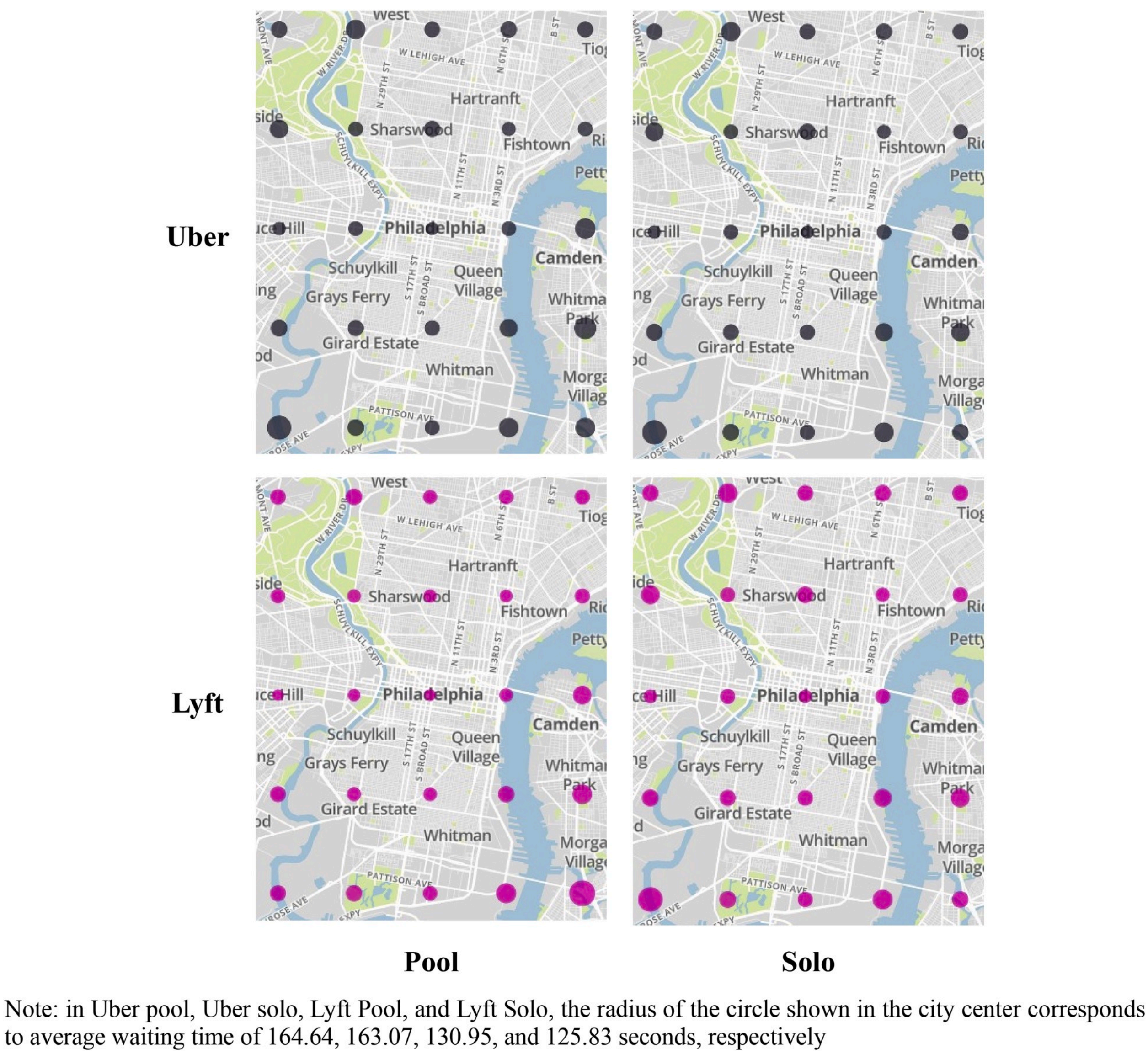

Fig. 1. Average Weekdays Pick-up Waiting Time (OVT) for Uber and Lyft
Note: in Uber pool, Uber solo, Lyft Pool, and Lyft Solo, the radius of the circle shown in the city center corresponds to average waiting time of 164.64, 163.07, 130.95, and 125.83 s, respectively.

are developed to help third-party developers to incorporate their services into their application. Through Uber and Lyft APIs, third-parties can estimate the ride fare range (i.e. low and high), the pick-up waiting time, the trip duration, and the trip distance for a given origin and destination offered by Uber and Lyft at the origin. Yahoo weather API provides up-to-date weather information for the given location.

This study covers an area of 8.5 by 14 miles around Philadelphia city center (Philadelphia city hall) (see Fig. 1). The study area is divided into 5 zones resulted in a 5 × 5 grid with 25 locations (points) as potential origin-destination nodes. This study grid is selected such that customers are able to request both solo and pool ride-sourcing services offered by Uber and Lyft. For our study, we collected ride estimates for solo and pool rides. To be sure, the study area covers locations with different road types and population densities. Ride data (trip duration, trip distance and fare range) was collected for hypothetical travels between any two points of the grid. Additionally, we collected pick-up waiting time, and weather conditions for any origin of the hypothetical travel. Note that both Uber and Lyft provide pick-up waiting times based on the origin of the trip, and therefore the pick-up waiting times do not depend on the trip destination.

Accessing Uber and Lyft APIs are free and therefore a very large dataset can be collected free of charge with an accurate pick-up and drop-off locations. Such collected data from Uber and Lyft are extensively used and trusted in studying ride-sourcing platforms (L. Chen, Mislove, & Wilson, 2015; Jiao, 2018; Shokoohyar et al., 2020; Wang & Mu, 2018). Uber and Lyft pick-up waiting time, travel time and trip fare are estimations based on GPS data collected from their cabs. Estimates can vary based on demand patterns and real-world factors like traffic or road construction. Uber and Lyft claim that these estimates are very close to the actual data, but they are not guaranteed (Golson, 2016; Joseph, 2018; Uber, 2019).

The data was collected in June 2018 which generated 1,004,344 trips in total (505616 Uber rides and 498728 Lyft rides). Collected attributes of the rid-sourcing trips are presented in Table 1. Pick-up waiting time refers to passengers' waiting time for their ride (OVT, i.e. Out of Vehicle Time), and trip duration refers to the travel time in the vehicle (IVT, i.e. In-vehicle Time).

2.2. Methodology

This research estimates the impact of several factors on the ride-sourcing platforms: trip origin and destination, pool or solo ride, weather condition, and trip distance.

In this section, first, the variables incorporated in the analysis are introduced. Table 2 summarizes descriptive statistics of these variables. Second, the contribution of these variables and the reason why they are incorporated in our analysis are discussed based on the literature. Third, three regression models are developed to study pick-up waiting time (model (1)), in-vehicle time (model ((2))) and trip fare changes (model ((3))). Fourth, the estimated models are presented, and evaluated while their coefficients are interpreted.

Since studies showed that ride-sourcing platform accessibility (pick-up waiting time) significantly depends on the origin related properties (Hughes & MacKenzie, 2016; Thebault-Spieker, Terveen, & Hecht, 2017; Wang & Mu, 2018), distance of origin and destination of each ride from the city center using haversine distance were also generated and added to our dataset. Haversine distance measures the great-circle distance between two points on a sphere given their longitudes and latitudes. We incorporate these variables to analyze the impact of location related properties such as road and population density on rides in the ride-sourcing network.

Table 1
Ride-sourcing trips' attributes.

Attribute	Description
Time	Time that the request is made
Provider	{Uber, Lyft}
Service	{Pool, Solo}
Origin	Origin latitude and longitude
Destination	Destination latitude and longitude
Pick-up Waiting Time (OVT)	In seconds
Trip Duration (IVT)	In seconds
Trip Distance	In Mile
Fare Range	(Low, High) In dollars
Weather Condition	Shower, Thunderstorms, Heavy Rain, etc.

Table 2
Summary of descriptive statistics.

Attribute	Provider	Number of Observations	Mean	Standard Error
Pick-up Waiting Time (OVT)	Uber	505616	270.40	0.18
	Lyft	498728	236.52	0.21
Trip Duration (IVT)	Uber	505616	1044.91	0.49
	Lyft	498728	1091.44	0.54
Fare	Uber	505616	14.19	0.008
	Lyft	498728	13.40	0.008
Trip Distance	Uber	505616	6.30	0.003
	Lyft	498728	6.60	0.004
Origin to City Center Distance	Uber	505616	4.59	0.002
	Lyft	498728	4.57	0.008
Destination to City Center Distance	Uber	505616	4.63	0.002
	Lyft	498728	4.63	0.008

Uber and Lyft both offer solo and pool rides. Their cheapest solo rides are called UberX and Lyft, respectively. In solo rides, each driver is matched and assigned to only one rider for the requested pick-up and drop-off location. On the other hand, in pool rides, riders can share the ride with others. On the other hand, pool rides are referred to as Uber-Pool and Lyft-line, respectively. In the pool ride, riders can enjoy the benefit of sharing the cost of the ride with others. However, these riders may face a longer trip duration and pick-up waiting time. During pool rides, several drop-offs and pick-ups may occur, which can result in a longer trip duration. Additionally, a driver who already has a rider in the car may not be able to freely modify the route of its ride to pick up a newly added rider. In this case, the new rider may face a longer pick-up waiting time compared to a solo ride. To control for the impact of ride type on the ride-sourcing platforms, we created indicator variables of UberPool, UberX, Lyft-line, and Lyft. In addition, using these variables, we compared Uber and Lyft in terms of pick-up waiting time, trip duration and fare.

Extreme weather conditions may significantly impact the ride-sourcing platform. Brodeur and Nield studied the impact of rainy weather conditions on the accessibility of Uber and taxi in the New York City (NYC) (Brodeur & Nield, 2017). They observe that Uber fare goes up when it's raining, which encourages higher supply. In turn, this increases the number of Uber rides compared to taxi rides. To study how the weather may impact ride-sourcing platforms. In the collected data, we observed 13 unique weather conditions during our data collection period: mostly cloudy, partly cloudy, cloudy, mostly clear, clear, showers, thunderstorms, scattered showers, rain, heavy rain, sunny, mostly sunny, and breezy. We categorize the weather conditions by creating an indicator variable called extreme weather condition. This indicator is equal to 1 when there is heavy rain, rain, showers, thunderstorms, or scattered showers and 0 otherwise. In our dataset only 8% of the data points are during the extreme weather and the occurrence of each extreme weather condition (heavy rain, rain, showers etc.) in our collected data is not enough to draw a conclusion regarding their exclusive impact on ride-sourcing platforms. Fig. 2 presents the frequency of weather conditions at each day. Note that this figure should be read vertically. In this figure, each cell represents the percentage of time a weather condition has occurred at each day. For instance, in the first column, on Jun 7th only 12% of the data points (ride-sourcing trip requested) were collected (completed) during the mostly clear weather condition. 34% and 31% of data points were collected during partly and

Weather Conditions		Thu 7	Fri 8	Sat 9	Sun 10	Mon 11	Tue 12	Wed 13	Thu 14	Fri 15	Sat 16	Sun 17	Mon 18	Tue 19	Wed 20
None extreme weather condition	Sunny	0	0	0	0	0	0.18	0	0.77	0.3	0	0	0	0.09	0
	Mostly Sunny	0	0	0	0	0	0.17	0	0	0.07	0	0	0	0.12	0.41
	Clear	0.01	0	0	0	0	0.26	0	0.17	0.1	0.03	0	0	0	0.1
	Mostly Clear	0.12	0.05	0	0	0.05	0	0	0	0	0	0	0	0.05	0.19
	Breezy	0	0	0	0	0	0	0	0.04	0	0	0	0	0	0
	Partly Cloudy	0.34	0.07	0.43	0	0.18	0.32	0.05	0	0.52	0.19	0.41	0	0.25	0.3
	Mostly Cloudy	0.31	0.19	0.54	0.13	0.13	0.04	0.43	0.01	0	0.78	0.59	0.84	0.17	0
	Cloudy	0.21	0.69	0	0.61	0.25	0.02	0.42	0	0	0	0	0.12	0.2	0
extreme weather condition	Scattered Showers	0	0	0	0.05	0	0	0.1	0	0	0	0	0	0.11	0
	Showers	0	0	0.03	0.04	0.01	0	0	0	0	0	0	0	0	0
	Rain	0	0	0	0.16	0.29	0	0	0	0	0	0	0	0	0
	Heavy Rain	0	0	0	0.02	0.1	0	0	0	0	0	0	0	0	0
	Thunderstorms	0	0	0	0	0	0	0	0	0	0	0	0.04	0	0

Fig. 2. Frequency of Weather Conditions at each Day (Jun 7th to Jun 20th).

mostly cloudy weather conditions. According to this table, we did not have extreme weather condition in different hours of the day (Jun 7th) and therefore, there is no related data points.

Hughes and MacKenzie observed that Uber's accessibility is higher during day time and lower during night time (Hughes & MacKenzie, 2016). To control the effect of time in our analysis, we incorporate time fixed effect. Several studies have shown that travel behavior differs during weekdays and weekends (Lockwood, Srinivasan, & Bhat, 2005; Soh et al., 2010). During weekend traveling and eating, followed by routines of daily life account for 60% of total weekend activities and work or school related activities are only about 4.5% of the total activities. On the other hand, work or school related activities are the common activities during weekdays (Zhong & Hunt, 2010). To control for the weekdays and weekends effect, we therefore run two separate Ordinary Least Squares (OLS) regression models by including only weekday or weekend observations. Using OLS, we analyze three dependent ride-sourcing platforms attributes: 1) pick-up waiting time (OVT) (1), 2) trip In Vehicle Time (IVT) (2), and 3) ride fare (3).

The fare included in our analysis (model (3)) is the average of low and high estimated fare. To make the coefficient tractable, variables are uniformly normalized in a range of 0–1. We denote data collected for a ride request from pick-up location (origin) denoted by o to drop-off location (destination) denoted by d at time t by subscript $(o,d),t$. In these models, T is 1×24 matrix of time fixed effect dummy variables and α is 24×1 matrix of time fixed effect coefficient. Note that the value of the n^{th} column of matrix T for observation $(o,d),t$ is 1 if the hour of the day that the data is collected is in a range of $[n, n+1)$ and 0 otherwise. In the following models, the error term is denoted by u. Uber and Lyft APIs provide pick-up waiting time (OVT) for any ride request based on the pick-up location, and the collected OVT is independent of the drop-off location. Therefore, in model (1), the subscript only depends on the pick-up location. The models' specifications are as follows:

$$\begin{aligned} OVT_{(o),t} = {} & \beta_0 + \beta_1[Origin\ to\ City\ Center\ Distance]_{(o),t} \\ & + \beta_2[Extreme\ Weather\ Condition]_{(o),t} + \beta_3[UberPool]_{(o),t} \\ & + \beta_4[UberX]_{(o),t} + \beta_5[Lyft]_{(o),t} + T_{(o),t}\alpha + u_{(o),t} \end{aligned} \tag{1}$$

$$\begin{aligned} IVT_{(o,d),t} = {} & \beta_0 + \beta_1[Origin\ to\ City\ Center\ Distance]_{(o,d),t} \\ & + \beta_2\ [Destination\ to\ City\ Center\ Distance]_{(o,d),t} + \beta_3\ [Distance]_{(o,d),t} \\ & + \beta_4[Extreme\ Weather\ Condition]_{(o,d),t} + \beta_5[UberPool]_{(o,d),t} \\ & + \beta_6[UberX]_{(o,d),t} + \beta_7[Lyft]_{(o,d),t} + T_{(o,d),t}\,\alpha + u_{(o,d),t} \end{aligned} \tag{2}$$

$$\begin{aligned} Fare_{(o,d),t} = {} & \beta_0 + \beta_1[Origin\ to\ City\ Center\ Distance]_{(o,d),t} \\ & + \beta_2\ [Destination\ to\ City\ Center\ Distance]_{(o,d),t} \\ & + \beta_3\ [Distance]_{(o,d),t} + \beta_4[Extreme\ Weather\ Condition] \\ & + \beta_5[UberPool]_{(o,d),t} + \beta_6[UberX]_{(o,d),t} + \beta_7[Lyft]_{(o,d),t} + T_{(o,d),t}\ \alpha \\ & + u_{(o,d),t} \end{aligned} \tag{3}$$

All models in our study performed well. They all passed the F test (p-Value< 0.001). Heteroskedasticity robust standard error was used in all models to avoid the concern of heteroskedasticity. The variance inflation factor (VIF) tests were applied to quantify the severity of multicollinearity, and the result shows that multicollinearity is not a significant issue in our models as the VIFs are all bellow 5.

Studying these three models can help TNC managers to better equilibrate demand with supply by implying that how demand changes may affect TNC performance (financial and non-financial). Generally speaking, demand in ride-sourcing platforms may decrease non-financial performance of TNCs such as pick-up waiting time and trip travel time as well as financial performance of TNCs, such as ride-sourcing trip fare. Furthermore, demand level may negatively depend on the availability of substitute services from competitors. Extreme weather conditions can also negatively impact both supply and demand affecting financial and non-financial performance of TNCs. All these relationships are numerically discussed in this study.

3. Model results

With respect to the OLS model estimation for the location grid, we analyze and compare Uber and Lyft platforms from three dependent attributes point of view: pick-up waiting time, trip in vehicle time, and fare.

3.1. Trip pick-up waiting time (OVT)

Fig. 1 represents average pick-up waiting time during weekdays in obtaining pool (left column) or solo (right column) rides from Uber (black circles in the top row) or Lyft (purple circles in the bottom row). The figure provides two main observations. First, the average waiting time is not uniformly distributed. In all figures, the average waiting time is lower in the city center, and it increases by getting further away from the city center. This observation indicates that more drivers are available in the city center compared to the areas around it. Second, comparing Uber and Lyft, we observe that Lyft is more accessible than

Table 3
OLS model result for pick-up waiting time (OVT).

Variables	Coefficient (*p*-Value)	
	Weekday	Weekend
Origin to City Center Distance	0.135 (0.00)	0.140 (0.00)
Extreme Weather Condition	0.015 (0.00)	−0.014 (0.00)
UberPool	0.026 (0.00)	0.021 (0.00)
UberX	0.015 (0.00)	0.009 (0.00)
Lyft	−0.007 (0.00)	−0.009 (0.00)
Intercept	0.035 (0.00)	0.038 (0.00)
Number of Observations	732345	271999
R-Squared	0.151	0.152

Note: Lyft line (pool) is considered as reference variable in regression models.

Uber. As there are no significant differences between average waiting pick-up time between weekdays and weekends, the figure shows that the average waiting pick-up times during weekends is omitted for space and is available upon request.

To formally test our observations, we run OLS regression in two models by considering weekdays and weekends separately (i.e. OLS model (1)). The regression summary is presented in Table 3, with waiting pick-up time as a dependent variable, and the independent variables shown in the first column. The coefficient of determination (R^2) shows that 15% of the variance in the pick-up waiting time is predictable from the independent variables. This model only includes origin to city center distance variable, weather condition and service type variables (i.e. UberPool, UberX, Lyft and Lyft line). Several studies have shown that pick-up waiting time significantly depend on the socio-demographic factors of the pick-up area like population density, minority rate, transportation infrastructure (Hughes & MacKenzie, 2016; Jiang et al., 2018; Shokoohyar et al., 2020; Wang & Mu, 2018). Including these factors may improve the prediction power of this model as well, however analyzing the impact of socio-demographic factors on the pick-up waiting time was not in the scope of this study.

Table 3 demonstrates four findings. First, the coefficient of Origin to City Center distance is positive and significant in both models. This result confirms that the waiting pick-up time is lower in the city center compared to locations around it during both weekdays and weekends.

Second, the coefficient of the Extreme Weather Condition is significant in both models. The coefficient is positive in the weekdays model, while, negative in the weekends model which indicates that extreme weather condition has an opposite impact on pick-up waiting time on weekdays and weekends. This can be due to the fact that during weekends, people's trips are mostly leisure-related and not mandatory. Therefore, an extreme weather condition may cancel leisure-related rides and decrease the ride demand. A decrease in the ride demand results in a lower pick-up waiting time. On the other hand, weekday rides are mostly work-related; therefore, are mandatory and cannot be canceled due to just extreme weather conditions. The extreme weather conditions during weekdays even increase the demand as people may try to avoid it by getting Uber or Lyft rides. An increment in the ride demand then increases the waiting time and decreases the accessibility of Uber and Lyft rides.

Third, in both models, it is observed that the estimated coefficient of pool rides is larger than solo rides for both Uber and Lyft. In pool rides, a driver cannot freely modify the route to pick up a new rider when he already has a rider in the car. This factor results in a higher waiting time of pool rides compared to solo rides.

Finally, based on the OLS results, it is indicated that Uber has a higher waiting time in both pool and solo rides compared to Lyft.

3.2. Trip in vehicle time (IVT)

In this section, we analyze the impact of the origin, destination, distance, and weather on the trip duration in separate models considering weekdays and weekends. The summary of the regression analysis (i.e. OLS model (2)) is presented in Table 4 with Trip duration as dependent variable and independent variables as shown in the first column.

Table 4
OLS model result for in vehicle trip time (IVT).

Variables	Coefficient (*p*-Value)	
	Weekday	Weekend
Origin to City Center Distance	−0.056 (0.00)	−0.044 (0.00)
Destination to City Center Distance	−0.048 (0.00)	−0.044 (0.00)
Trip Distance	0.866 (0.00)	0.771 (0.00)
Extreme Weather Condition	0.002 (0.00)	−0.001 (0.00)
UberPool	−0.004 (0.00)	−0.005 (0.00)
UberX	−0.004 (0.00)	−0.005 (0.00)
Intercept	0.179 (0.00)	0.169 (0.00)
Number of Observations	732345	271999
R-Squared	0.675	0.689

Note: Lyft line (pool) is considered as reference variable in regression models.

The OLS model results on IVT reveals five main points. First, the negative and significant coefficients of Origin to City Center Distance and Destination to City Center Distance show that the trip duration of a ride is on average higher when entering the city center compared to leaving the city center. This can be due to the occurrence of more traffic congestion events in the downtown area. Second, the positive coefficient of distance shows that trip duration increases in the distance between the origin and the destination. Third, extreme weather conditions have a positive impact on the trip durations in weekdays; while it has a negative impact in weekends. This result follows the same logic explained in the impact of weather conditions on pick-up waiting time. The extreme weather condition increases demand in weekdays and results in more trips. More trips then lead to a higher road congestion and, consequently, increase trip durations. On the other hand, extreme weather condition decreases the demand during weekends, leading to a lower road congestion and reducing trip durations. Fourth, on average, Uber pool rides have longer trip durations compared to the Uber solo rides. This can be due to the several pick up and drop off riders that share a same trip together. However, there is no significant difference between Lyft line and solo rides in terms of trip duration. Fifth, Uber's service is faster compared to Lyft in both pool and solo rides.

3.3. Trip fare

The impact of trip origin, destination, and weather on fares offered by Uber and Lyft is discussed in this section. The result of the OLS model (3) is presented in Table 5 with the independent variables shown in the first column.

Comparing weather condition coefficients across models, the coefficient of the Extreme Weather Condition is positive in the weekdays model; while, it is negative for the weekends model. Following the logic in the above discussions of the impact of weather condition on pick-up

Table 5
OLS model result for trip fare.

Variables	Coefficient (*p*-Value)	
	Weekday	Weekend
Origin to City Center Distance	−0.012 (0.00)	−0.012 (0.00)
Destination to City Center Distance	0.003 (0.00)	0.002 (0.00)
Trip Distance	0.376 (0.00)	0.365 (0.00)
Extreme Weather Condition	0.006 (0.00)	−0.008 (0.00)
UberPool	0.019 (0.00)	0.016 (0.00)
UberX	0.055 (0.00)	0.049 (0.00)
Lyft	0.050 (0.00)	0.046 (0.00)
Intercept	0.006 (0.00)	0.016 (0.00)
Number of Observations	732345	271999
R-Squared	0.691	0.657

Note: Lyft line (pool) is considered as reference variable in regression models.

waiting time, demand increases in the extreme weather condition during weekdays and decreases during weekends. During weekdays, the higher demand during extreme weather conditions results in higher fares compared to the normal weather conditions. On the other hand, during the weekends, the extreme weather conditions result in lower demand and, in turn, leads to lower fares compared to the normal weather condition. This observation shows that Uber and Lyft fare adaption policies are demand sensitive, and they adjust fares to match supply with demand.

Looking at each model separately, the analysis reveals four main observations. First, the model results indicate that trips leaving the city center have a higher fare compared to the same trip heading toward the city center in both weekday and weekend. Higher fares in the city center attract more drivers and, in turn, result in a quicker pick-up waiting time. Note that this result provides a logical reason for our finding regarding the waiting time in the pick-up waiting time (OVT) model. In other words, model results for OVT denote that pick-up waiting time is not uniformly distributed around the city, and waiting time decreases by getting closer to the city center. Second, the positive and significant coefficients of distance show that fare increases in the trip distance. To compensate drivers for the trip driving distance, ride-sourcing platforms charge fares based on trip distance. Third, we observe that pool rides are cheaper than solo rides in both Uber and Lyft. This observation is because in the pool rides, the riders are sharing the cost of the ride among themselves. Fourth, Lyft offers a lower fare compared to Uber.

3.3.1. *The per mile trip fare (pool vs. solo)*

To study the impact of services types on per mile trip fares, the regression model in Section 3.3 has been modified by incorporating the interaction variables of the service type and the trip distance. The results of this new regression model are presented in Table 6 and the independent variables are shown in the first column.

Note that the estimated coefficients of Origin to City Center Distance, Destination to City Center Distance, and Extreme Weather Condition are approximately the same in both Tables 5 and 6. This observation shows that incorporating the interaction variables does not impact these variables and therefore the coefficient interpretations are the same as what is explained in Section 3.3. The results presented in Table 6 reveal two main points. First, the fixed fare for UberX and Lyft riding services are, respectively higher compared with the UberPool and Lyft line. Second, in comparison with the UberX and Lyft, the per mile fare of UberPool and Lyft line (pool services for both Uber and Lyft) are respectively lower. These two findings can be used together in order to determine the optimal strategy based on the trip distance. Fig. 3 shows estimated trip fare based the model presented in Table 6 for a hypothetical trip with the city center as its destination. These figures show that during weekdays UberX is cheaper than Lyft when the trip distance is less than 2.2 miles, and otherwise Lyft is cheaper. During weekends UberX is cheaper than Lyft when trip distance is less than 4.1 miles and Lyft is cheaper otherwise. The results also show that Lyft line always dominates all other type of services. These findings can be used to help riders to make a wiser travel decision for short and long trips.

Table 6
OLS model result for trip fare with interaction variables.

Variables	Coefficient (*p*-Value)	
	Weekday	Weekend
Origin to City Center Distance	−0.012 (0.00)	−0.013 (0.00)
Destination to City Center Distance	0.003 (0.00)	0.002 (0.00)
Trip Distance	0.345 (0.00)	0.307 (0.00)
Extreme Weather Condition	0.006 (0.00)	−0.008 (0.00)
UberPool	0.019 (0.00)	0.009 (0.00)
UberX	0.040 (0.00)	0.026 (0.00)
Lyft	0.041 (0.00)	0.030 (0.00)
UberPool × Trip Distance	−0.004 (0.00)	0.037 (0.00)
UberX × Trip Distance	0.082 (0.00)	0.119 (0.00)
Lyft × Trip Distance	0.047 (0.00)	0.079 (0.00)
Intercept	0.006 (0.00)	0.027 (0.000)
Number of Observations	732345	271999
R-Squared	0.696	0.665

Note: Lyft line (pool) and Lyft line × Trip Distance is considered as reference variable in regression models.

4. Concluding remarks

This study investigates the effects of weather conditions and types of ride-sourcing services on the financial and non-financial performances of Uber and Lyft as two popular TNCs in the city of Philadelphia, in the U.S. Three data driven models were constructed to predict trip fare (ride fare), trip in vehicle time (IVT) and pick up waiting time (OVT) with respect to given input variables during both weekdays and weekends. Summary of the results is presented in Table 7.

In this table, pick-up waiting time, and in vehicle time are in seconds and ride fare is in US dollars. Origin to City Center Distance, Destination to City Center Distance and Trip Distance are in miles, and the other independent variables are indicator variables (i.e. takes the value of 0 or 1). Each cell in Table 7 presents the coefficients of variables based on the result presented in Tables 3–5 Note that Tables 3–5 present estimated coefficients based on uniformly transformed data, but in Table 7, coefficients are converted back to the actual ones with the units as explained above. For instance, 27.75 in the first column of the first row shows that during weekdays the pick-up waiting time increases by 27.75 s when the distance of origin to city center increases by 1 mile.

In terms of non-financial performance indexes, our study shows that extreme weather conditions (i.e. shower, heavy rain) significantly impact riders demand. Demand increases due to the extreme weather during weekdays, while it reduces during weekends. These opposite findings may relate to the purpose of the trips. During weekdays, trips are more work-related and therefore mandatory. Due to the extreme weather conditions, more customers may request rides to avoid getting affected by the extreme weather condition. However, trips are more leisure-related during weekends which makes customers be more flexible. Leisure-related trip may get canceled due to the extreme weather condition which in turn decreases the demand. Our study shows that demand positively impacts pick-up waiting time and the duration of trips. In particular, according to Table 7, during weekdays the pick-up waiting time and trip duration are on average 21.6 and 6.66 s longer during the extreme weather conditions, respectively. On the other hand, pickup waiting time and trip duration are on average 20.16 and 3.33 s shorter during the extreme weather conditions, respectively.

As discussed above, this study confirms the significant effect of the extreme weather conditions on the ride-sourcing platforms, in particular, its impact on average pick-up times, and trip durations. TNC managers may integrate weather conditions and their consequences on riders' behaviors in adjusting the dynamics of ride-sourcing services. For instance, they may focus on offering more cost-wised services, such as pool rides, depending on the demand volume. In high demand time, offering more affordable pool services compared to the solo rides helps TNCs to satisfy more demand. Therefore, such an increase in supply would improve riders experience in terms of pick-up waiting time. On the other hand, offering more pool services may increase TNCs profit by increasing their revenue. Finally, by forecasting weather and providing in-advanced incentives and promotions, TNCs may increase the supply of drivers during the high demand times.

The results of this study show that Lyft riders wait less than Uber ones in receiving ride-sourcing services. According to Table 7, during weekdays, Lyft (Lyft line) riders on average wait 31.68 (37.44) seconds less than UberX (UberPool) riders. Furthermore, during weekends, Lyft (Lyft line) riders on average wait 25.92 (30.24) seconds less than UberX (UberPool) riders. On the other hand, Uber provides faster ride-sourcing services compared to Lyft. Uber's services are on average 13.32 and 16.64 s faster than Lyft during weekdays and weekends, respectively. Both Uber and Lyft are more accessible in the city center compared to

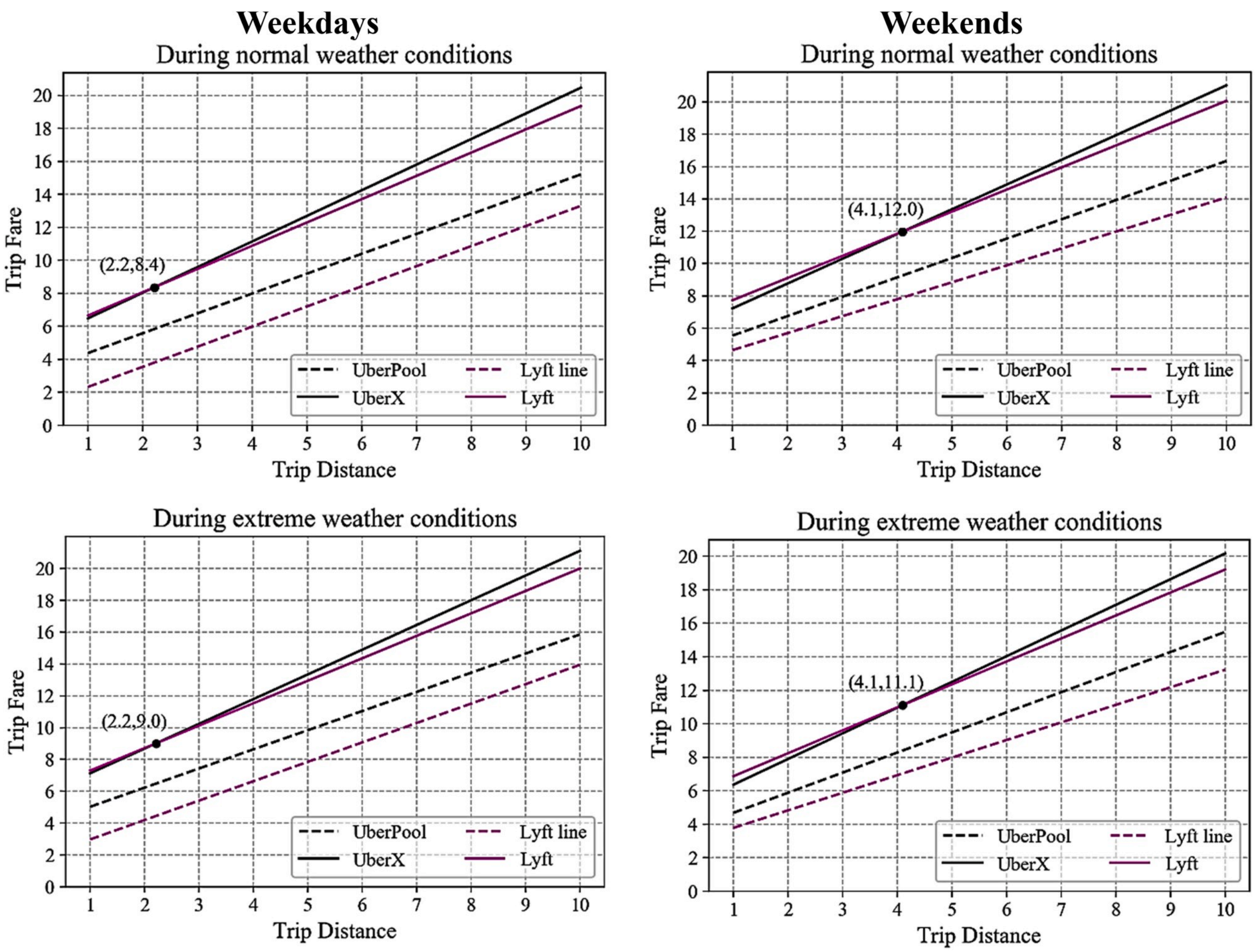

Fig. 3. Trip fare based on the estimated model (A hypothetical trip with city center as its destination).

Table 7
The effects of weather conditions, origin-destination locations, distance, and types of ride-sourcing services on financial and non-financial performances of Uber and Lyft.

Variables		Pick-up waiting time (in seconds)		In Vehicle Time (in seconds)		Ride fare (in US dollars)	
		Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends
Location	Origin to City Center Distance	27.75	28.77	−26.61	−20.91	−0.18	−0.18
	Destination to City Center Distance	NA	NA	−22.81	−20.91	0.05	0.03
	Trip Distance	NA	NA	108.91	96.96	1.53	1.48
Weather	Extreme Weather Conditions	21.6	−20.16	6.66	−3.33	0.65	−0.86
Ride-sourcing	UberPool (Pool)	37.44	30.24	−13.32	−16.64	2.05	1.72
	UberX (Solo)	21.6	12.96	−13.32	−16.64	5.92	5.28
	Lyft (Solo)	−10.08	−12.96	No difference	No difference	5.38	4.95

Note: Lyft line (pool) is considered as reference variable in regression models.

the suburb areas. Pick-up waiting time increases in Origin to City Center Distance by 27.75 and 28.77 s per mile during weekdays and weekends, respectively. This result shows that drivers are more attracted to the city center as demand is more stable in this highly populated area. To balance the service network, TNC managers may provide incentives for their drivers to be more accessible in different city areas.

Trip duration (In Vehicle Time) decreases in Origin to City Center Distance and (Destination to City Center Distance) by 26.61 (22.81) and 20.91 (20.91) seconds per mile during weekdays and weekends, respectively. This observation shows that trips that are closer to the center city are taking longer. Additionally, trip duration increases in trip distance by 108.91 and 96.96 s per mile during weekdays and weekends, respectively. Drivers on average drive with speed of 33.05 and 37.12 mile per hour during weekdays and weekends, respectively. This shows that drivers drive 4.07 miles per hour faster during weekends compared to weekdays. This observation shows that traffic is slightly lighter during weekends when compared to weekdays and therefore drivers are able to drive faster.

In terms of financial performance, riding fare increases in the extreme weather conditions by 65 cents during the weekdays and decrease by 86 cents during the weekends. Trip fare decreases (increases) in Origin to City Center Distance (Destination to City Center Distance) by 18 and 18 (5 and 3) cents per mile during weekdays and weekends, respectively. For a same trip, getting a ride from the city center is pricier for both Uber and Lyft services compared with the suburb areas. The higher fare in the city center attracts more drivers and in turn leads to a higher ride sharing availability in the city center. Additionally, Uber and Lyft riders on average pay 153 and 148 cents per mile during weekdays and weekends, respectively. Furthermore, Lyft Pool and Solo fares are on average less expensive than similar types of service offered by Uber.

An unbalanced ride-sourcing network may reduce the satisfaction of riders in using TNC services and in turn reduce TNC's market share. TNC riders may look for more accessible types of transportation (e.g., traditional taxi services or buses) in areas and times that TNCs are less accessible. Employing incentives (other than increasing riding fare) such as reward programs for drivers may improve the balance of the service network. These reward programs may be set up differently for solo or pool services to cover uniformly all city areas. These reward programs may also be used for riders to keep them as loyal customers. For instance, a reward program for TNC riders may include giving extra points or coupons when their trip durations significantly increase due to traffic jams in high demand locations, or long pick-up waiting times in low/medium demand locations.

The results of such a study completed in this paper let TNC companies collaborate with city transportation planners to use ride-sourcing as a completing transportation system, along with public transit systems in cities. This cooperation provides a win-win situation by providing better transportation services. City planners may provide incentives for Uber and Lyft to supply more frequent services for city areas around the city center rather than developing costly public transits for those locations. Uber and Lyft may include these incentives to have a more accessible service for those locations.

5. Future research

This study assessed the effects of weather conditions, demand locations, and types of ride-sourcing services on both non-financial and financial performances of Uber and Lyft as two popular TNCs in the city of Philadelphia, U.S. Findings of this research provide valuable insights into understanding riders' and drivers' behavior and in turn in balancing supply and demand in the ride-sourcing service networks. This study was limited to some locations in Philadelphia during the month of June 2018. For future research, more data can be collected in different locations while including other factors affecting traffic of roads, pick-up waiting times, trip durations, and riding fares, such as rush hours. Additionally, in the current study the data is collected from June 7th to June 20th, in summer 2018, and as a result the number of unique weather conditions occurred during this time frame are limited. It is worth to expand the time frame in order to collect more data and directly study the impact of each weather condition. It will also be interesting to incorporate seasonality and explore its impact on the ride-sourcing platforms. As another promising future research question, by collecting data from public transit systems and traditional taxi systems, city transportation planners, TNCs managers, and traditional taxi managers may have better ideas about riding performances in Philadelphia. This eventually may improve collaborations among them in providing better riding services throughout the city.

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