Research in Transportation Business & Management 29 (2018) 101–107

Contents lists available at ScienceDirect

Research in Transportation Business & Management

journal homepage: www.elsevier.com/locate/rtbm

Investigating Uber price surges during a special event in Austin, TX

Junfeng Jiao

Urban Information Lab, School of Architecture, The University of Texas at Austin, Sutton Hall 3.120, Austin, 78712, TX, United States

ARTICLE INFO

Keywords:
Uber
Price surge
Transportation networking companies (TNCs)

ABSTRACT

The purpose of this study was to evaluate the characteristics of Transportation Network Company (TNC) Uber's surge pricing during a special event. Using data collected using Uber's developer API over the 2015 Fourth of July weekend, this research investigated the form of price surge multipliers during periods of high demand. Regression models showed surge price was not correlated with ride wait time for July 3, July 4, or July 5, but it was correlated with ride request time in all three nights. July 4 had the strongest correlation and more instances of surge pricing, and those instances were greater in magnitude that the other evenings studied. This research has practical implications for transportation planners in that it reveals the obscurity of the price surge mechanisms. The unpredictability and lack of transparency surrounding surge pricing poses challenges for those working to incorporate TNCs into a city's transportation operations.

1. Introduction

Ridesourcing is a form of transportation growing in popularity in American cities. Sometimes called transportation networking companies (TNCs), these operations connect riders to drivers with cars via smartphone applications. Epitomized by companies such as Uber, Lyft, and many others, these operations use algorithms to match rider with driver to provide automobile transportation within service areas. Beyond connecting rider and driver, these services also facilitate cashless payments via credit card information provided by the rider. Payment policies and driver compensation rates vary across companies and according to area of operation, time of ride, length of ride, and other factors that are not necessarily transparent to the customer and the outside observer. During times of high usage, Uber and Lyft will enhance their prices to reflect this demand via a surge multiplier. According to communications released by Uber, this pricing is meant to attract more drivers into service at certain times, while also reducing demand on the part of riders (Uber, 2015) (Fig. 1).

Tensions between these companies, civic governments, and taxi cab companies are not uncommon, with the public sector and established industries reacting to the entry of a competitor that is often perceived as having fewer regulatory burdens. These objections also tend to center on concerns about safety for passengers, given that the companies perform their own background checks, while public transportation has city supervision and taxi cabs are subject to regulation, while others find that the surge pricing may not be transparent nor fair. In particular, the aftermath of Uber surge pricing in New York City in 2012 after Hurricane Sandy put the company on the defensive. After removing surge pricing "for most of the day after Sandy," the company took to its website to explain that surge pricing would need to be reinstated for operations to work (Casabien, 2012). In another investigation into surge pricing undertaken by the Washington Post, staff writer Nicholas Diakopoulos found that the pricing mechanism moved drivers already on the road to specific locations of high demand rather than attract new drivers to the road in Washington DC (Diakopoulos, 2014).

While Washington DC and New York City provide high profile examples of the tensions surrounding Uber, Austin, Texas provides a sufficient environment to study this pricing algorithm due to the popularity of car transportation, number of local and high profile events, and the civic opposition to the services. Despite an initial ban from operations in Austin in 2013, Uber and Lyft initiated their services anyway (Wear, 2013). Although the City of Austin publicized the prohibition of unpermitted ground transportation operations prior to the South by Southwest (SXSW) film, media, and music conferences in 2014, demand for the services during the festival prompted Uber surge pricing that surpassed the $150 mark (Bercovici, 2014). Despite these high prices and the failure of the Austin City Council to provide ground permits for rideshare, Uber and Lyft continued operations, developing a customer base and political contingent that advocated for their legal operation within the city (Wear, 2014a). The first major victory for the TNCs came in October 2014, when the City Council came to an interim agreement allowing for limited operations, and continued making progress in the institutionalization of their services with an agreement with Austin-Bergstrom International Airport ahead of the SXSW conferences in March 2015 (Wear, 2014b; Wear, 2015a, 2015b). Austin has continued to grapple with Uber, Lyft, and other TNCs in the city. In

E-mail address: jjiao@austin.utexas.edu.

https://doi.org/10.1016/j.rtbm.2018.02.008
Received 23 September 2017; Received in revised form 2 January 2018; Accepted 21 February 2018
Available online 26 February 2018

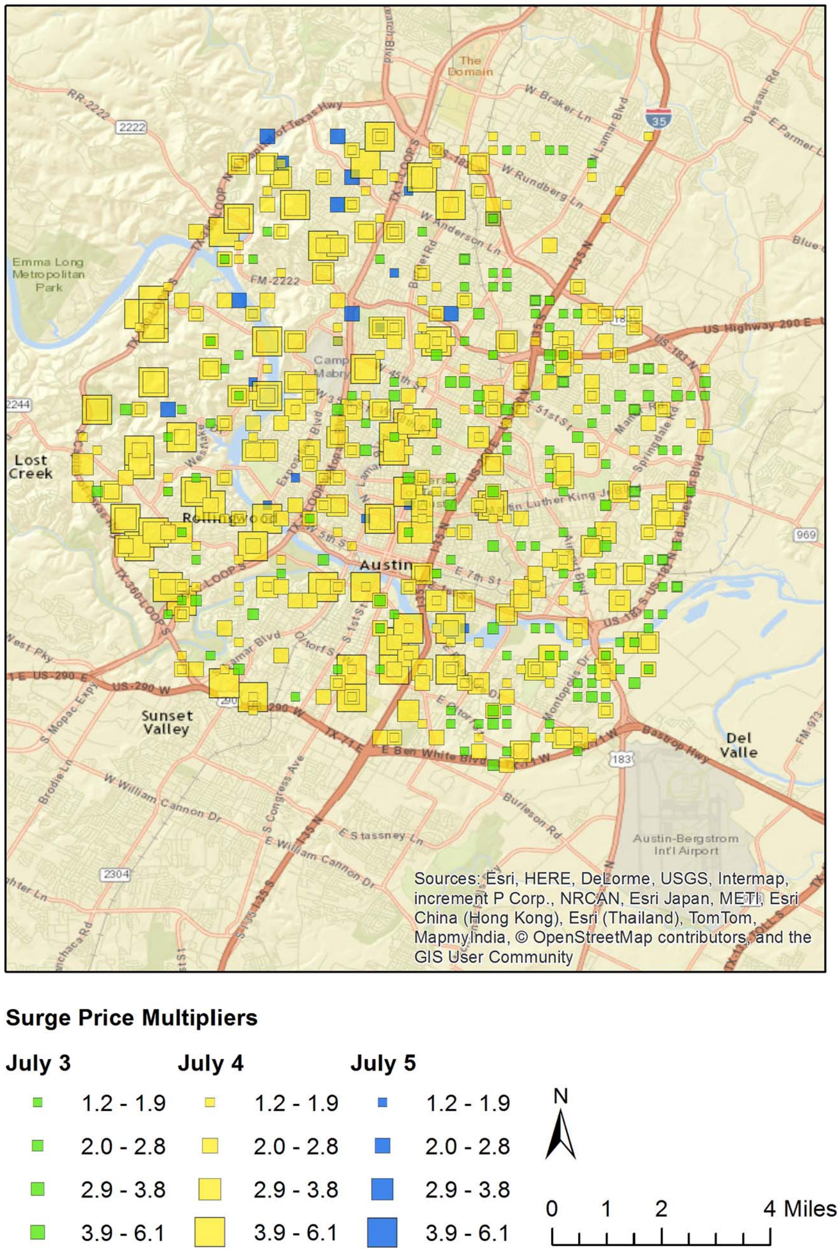

Fig. 1. Uber Surge Price Multipliers during the July 4th Weekend, 2015 in Austin, Texas.

December 2015, Austin's City Council approved rules requiring that all drivers working with ride-hailing apps must undergo fingerprint base background checks, which was upheld after voters rejected Lyft and Uber's Proposition 1 campaign (Hicks & Wear, 2016). As a result, Uber and Lyft stopped their operations in Austin in May 2016. After a year of campaigns from both companies, Texas State Legislature passed the House Bill 100 and overturned local ordinances on ride-hailing laws, which resulted Lyft and Uber's return to Austin in May of 2017 (Wear, 2017).

Several areas of TNC operation in Austin are attractive for study, including the relative safety of traditionally permitted ground transportation TNCs and price and operation style of TNCs within the greater transportation landscape. In regards to transportation planning and the built environment, the privatization of shared transportation options presents a conundrum, as its pricing model is not transparent and its business model is not as regulated and responsive to city policy as that of taxicabs. In Austin, Taxicab and limousine services (e.g. fare and permit) are regulated by city code. For example, there is minimum taxicab fare for trips originated from the airport and the current meter Taxicab rate is $2.50 for the first 1/6 mile plus $0.40 for each additional 1/6 mile. The minimum charge for limousine service is $55 per hour (City of Austin, 2017). Different with Taxicabs, Uber and other TNCs can choose their own rates, control their data and pricing info. These pose challenges for city official, transportation planners and other transportation operators.

Understanding the form and context of surge price multipliers is an important first step in determining policies and accounting for the role of rideshare in the city's transportation ecosystem. The ease of discovering and interpreting these pricing algorithms has tangible implications for policy makers and regulators who are tasked with incorporating this transportation system into the existing regulatory framework to improve access and equity.

Understanding surge pricing multipliers and their effect on ridership demand, driver supply, and effects on transportation business models going forward is particularly important for transportation managers. Uber and other TNCs completely interrupted the traditional taxicab business model (Cohen & Kietzmann, 2014; Jong & Dijk, 2015). These technology-responsive, TNC businesses also challenge public transit systems, which are public entities that typically respond to change slowly. While TNC apps have, to a certain extent, replaced public transit trips in metropolitan areas, understanding how surge multiplier pricing during special events affects ridership can help transit managers devise strategies where TNCs are complementing public transit, as opposed to competing with it (Rayle, Dai, Chan, Cervero, & Shaheen, 2016).

Greater understanding of the constantly evolving technology utilized by TNCs is also critical for transportation business managers going forward. TNCs are just one branch of the new sharing economy, which burgeoned as the internet and social media became more ubiquitous. There are two central tenets driving the sharing economy, which represents a societal shift from ownership model to an access model, 1) reduction of transaction costs and 2) efficient allocation of resources (Redfearn, 2016). However, as technology evolves and governing bodies continue to grapple with how to regulate the shared economy, business managers will also have to be able to adapt. Understanding how TNC technology informs and affects supply and demand price elasticity will help business managers stay ahead of the competition. This paper investigates the form of Uber surge pricing in Austin, Texas during the Fourth of July holiday weekend from July 3rd through July 5th, 2015. Researchers predicted that the convergence of a free public event, an Uber discount, a weekend, and a holiday would provide the conditions in which sustained price surges would occur, and would present the opportunity to decipher patterns lending insight into the pricing algorithm.

2. Literature review

Due to the newness of TNC ventures, the body of literature directly relating to their operations is scarce, with most works being published in 2013 or later. Of those works focused on regulation and environmental considerations comprise the main areas of study. Additionally, a growing number of research studies concern themselves with using data mining for transportation planning.

Early studies about technology and ridesharing centered on mechanisms like carpooling, which is quite different with TNC service. This literature expanded to consider carsharing like Zipcar and car2go. Prior to the introduction of rideshare and carshare, several studies investigated the use of technology to facilitate forms of carpooling. Notably, Golob and Giuliano (1996) examined an initiative to link carpoolers and drivers using landline telephones in Los Angeles in 1994 and 1995. The researchers concluded that the initiative was a failure. However, Dailey, Loseff, and Meyers (1999) found that a 1996 program in Seattle matching riders and drivers through the internet was as effective as traditional carpooling, and that the internet-enabled version reached a different population segment than those who would have participated in conventional carpooling. Morency's (2007) investigation of carpooling in Montreal from 1987 to 2003 found that carpooling as a whole declined over that time period and calls for new ways to reduce car usage. Studies on Zipcar and car2go have found that these companies may reduce the greenhouse gas emissions associated with car ownership (Firnkorn & Müller, 2011; Martin & Shaheen, 2011) as well as the overall number of vehicles owned (Martin, Shaheen, & Lidicker, 2010). Another report noted that the use of technology, such as smartphones, to optimize individual transportation logistics could result in the reduction of up to 190 million tons of carbon dioxide emissions by 2020 (Global eSustainability Initiative, 2008).

Rayle et al.'s (2016) San Francisco study found that TNC services satisfy a hitherto unmet need for transportation, as use of the services does not simply replace that of taxi cabs. The research team concluded that TNCs can either complement or supplant the use of public transportation. Similarly, Anderson (2014) concluded from surveying San Francisco drivers that driver behavior and characteristics likely determines whether these services add or subtract from a city's overall vehicle miles traveled (VMT). Full time drivers are likely to increase overall VMT, as they chase fares, while occasional drivers are more likely to integrate passengers into their daily driving habits, thus reducing overall VMT. From a legal perspective, Daus (2013) evaluates existing rideshare policies in several US cities and provides draft regulatory language concerning rideshare companies in order to address apprehensions regarding insurance, consistent fares, background checks and vehicle quality. Strong (2015) expands upon the legal perspective on TNCs by advocating for the inclusion of potential benefits and detriments to the environment when crafting regulatory policies. Miller (2016) suggests that the sharing economy, including TNCs, may induce an additional demand for services rather than simply overtake a traditional market share of taxi cab or public transportation demand. The literature on rideshare services and their role in special event organization is still limited (Currie, 1997; Frantzeskakis, 2006; Roche, 1994). However, there has been some research on transportation planning for special events. As cities grow, the number of special events will also increase, especially since many cities bid to host special events due to the boost in revenue they provide across multiple industries (hotels, restaurants, local retail, etc.). Robbins, Dickinson, and Calver's (2007) study provided a conceptual framework for transportation planning during special events, commenting on mechanisms that could facilitate sustainable travel and reduce traffic congestion. Uber and other TNC services play a large role in providing additional transit options, especially in areas where public transit isn't accessible, and must be considered as part of a larger transportation strategy during special events.

The literature on Uber's dynamic pricing strategy is still relatively new. Heiskala, Jokinen, and Tinnilä (2016), analyzed crowdsensing-based transportation services from a business model and sustainability view and determined that one of the biggest challenges for these new multi-sided market industries is getting pricing right. These industries are “winner-take-all” and pricing is key, since consumers usually don't want to get involved trying out too many networks (Heiskala et al., 2016). Uber's justification for its surge pricing multiplier is that it reduces demand by pricing out some riders while simultaneously induces supply by increasing the number of drivers on the road (Gurley, 2014). While some research is mixed, in general surge pricing does appear to control both supply and demand while keeping wait time consistently under 5 min (Chen & Sheldon, 2016). However, Chen, Mislove, & Wilson's, 2015 study also showed that surge pricing is noisy, often not lasting more than 5 min, and that it has only a modest effect on driver supply while a large, negative impact on ridership demand. Lee, Kusbit, Metsky, and Dabbish (2015) found that drivers found surge pricing to be unclear and desired greater transparency. Driver motivation also factored into whether surge pricing affected a driver's decision to respond to surge pricing.

Miller also considers the regulatory landscape for all aspects of sharing economy (e.g. TNC and Airbnb). Miller suggests that these industries within the realm of the sharing economy should require a separate set of regulations specifically crafted for them and that they should not fall under the same regulatory schemes that govern their older or more traditional economic counterparts (i.e. taxis for Uber, hotels for Airbnb) (Miller, 2016). This philosophy is shared by those in city planning (Cohen & Kietzmann, 2014).

3. Research design

Given the many concerns of regulators and civic governments, along with conclusions from researchers that TNCs may replace some public transit trips (Rayle et al., 2016) or induce more rides (Miller, 2016), it is important for planners to evaluate how these services work so that they may be integrated into local transportation systems (Cohen & Kietzmann, 2014). This integration and evaluation becomes especially pertinent when considering diversion of demand from public transportation to these private companies. Because access to smartphone technology varies, as does the public's ability to pay for surge pricing, an over-reliance on these ridesharing companies by city governments and transportation authorities could have implications for transportation access and equity. Therefore, understanding how demand pricing works becomes an essential first step for the incorporation of these services into greater transportation systems.

This research investigates Uber surge pricing in Austin, Texas as it occurs during a holiday weekend in order to understand its characteristics during times of high demand. The intention behind this research design is two-fold. First, Austin has a growing reputation as a destination for events like Austin City Limits Music Festival, South by Southwest, and other conferences and events that ostensibly create the conditions for a price surge. Second, given the car-based transportation environment of the city and its rapid population growth, all solutions and alternatives, including rideshare, should be considered (Wear, 2014a, 2014b). The ride price charged by TNCs is an important component, both for visitors and commuters within the city.

The holiday weekend including July 4, 2015 was chosen for study. The holiday itself fell on a Saturday, and a large civic celebration including a symphony and a fireworks show took place downtown in an area with limited parking and capacity for personal vehicles. In addition, Uber offered discount pricing of up to $20 off a ride on July 4, 2015 for first time riders who entered a specific promotional code into their smartphone apps. This promotion was advertised on the website for the event. Together, these factors created the conditions to study periods of high demand for Uber's services, providing what researchers determined would be an ideal opportunity to deduce the mechanisms of surge pricing.

4. Data and analysis

The data for this study was acquired through the development of a script that was used to ping Uber's application programming interface (API). Uber's API was developed by the company in order to provide third-party smartphone application developers with a tool that could be incorporated into transportation-related services. This tool allows an outside enterprise, or in this case, researcher, to collect real-time information on hypothetical rides from an origin point to a destination via latitude and longitude coordinates. The data collected from Uber included an estimated price range for the generated trip, a ride distance, an estimated waiting pick-up time, and a price surge multiplier for each form of Uber transportation service available in Austin: UberX, UberXL, and UberSelect.

UberX, which is the default service form, is the least expensive model with the widest variety of vehicle types. UberXL requires larger vehicles that command a higher price, and UberSelect provides service in vehicles of a higher price point at an elevated cost to the rider. The price range for each form of transportation services varies as well. Price ranges for the cost estimates vary, with longer trips and surge priced trips generally providing the greatest ranges. The Uber API allows for the collection of 1000 data requests per hour. Each ride request returns the price point for each of Uber's service models: one for UberX, one for UberXL, and one for UberSELECT. This effectively turns a single ride request between the origin and destination into three data requests to Uber. Surge price results are returned as a multiplier, with a value of 1 indicating that no surge pricing has occurred, whereas a surge multiplier of 3.2 would indicate that the estimated price is 3.2 times greater than it would be during a time of less demand.

Using Uber's API, researchers were able to collect data on hypothetical rides between points in Austin from 7:11 am on Friday, July 3, 2015 until 5:41 am on Tuesday, July 7, 2015, though several gaps in data occurred due to computer errors. The study area of the city included was defined as the areas between coordinates 30.37963, −97.8304 (northwest point), 30.19791, −97.6426 (southeast point), 30.37963, −97.6426 (northeast point), and 30.19791, −97.8304 (southwest point). This created a box over the Austin area with sides approximately 12.5 miles in length. Uber does not operate within the political or statistical bounds of the City of Austin, the Austin-Round Rock-San Marcos metropolitan area, or Census block groups. In addition, the irregular shape of these conventional geographic zones complicated the process of requesting data. Therefore, the researchers chose to evaluate a rectangular area with specific and uniform meridians and parallels. The resulting area forms an approximate rectangle that includes most of downtown and central Austin, as well as a few important suburban neighborhoods.

The study area was then divided into a 50 by 50 grid, creating 2500 areas of potential start and end points. In order to minimize erroneous samples, researchers ensured that the origin and destination points achieved a minimum distance apart, and that those points would have to be traversed by road networks. This prevented a reliance on pure random coordinate generation that could have produced a route with no distance, and therefore would have skewed pricing and surge results. The algorithm designed to this grid structure guaranteed that origin and destination points were randomly selected from distinct areas of the 2500 grid. This provided a sample set of diverse, random routes within an area covering 156.25 mile^2 of the Austin metropolitan area.

Of the 46,827 data requests collected, 3295 were discarded from the dataset due to mismatches between the time request data and the price request data. The remaining 43,532 entries were filtered into times that represented times of nightlife, from 10:00 pm until 2:30 am for July 3 through July 6, 2015. This provided three nightlife points of study: Friday, July 3, Saturday, July 4, and Sunday, July 5. The data was narrowed down to these smaller study areas in order to provide a better characterization of price surge mechanisms and to avoid an over-dependence on large datasets that may not prove useful to the study (Crampton et al., 2013; Shelton, Poorthuis, & Zook, 2015).

Because the goal of this research was to understand the basic mechanisms behind surge prices during events, this study limited its investigation to descriptive statistics, simple regression analyses, and GIS data visualization for the three nights studied (Vogel, Greiser, & Mattfeld, 2011). Uber is growing in popularity, yet retains private ownership and does not provide cities and transportation planners with its pricing algorithms. The simplicity of the study was by design; in order for transportation planners to adapt to the entry of a new form of transport, they must be able to predict pricing schemes with a relative level of ease. Simple linear regression models were calculated for each night to predict surge multipliers based on: 1) estimated ride wait time and 2) ride request time. Uber estimated ride wait time refers to the waiting time would be experienced by the passenger, measured in seconds, between requesting a ride and driver pick-up. In the following sections, both ride fare and wait time always refer to the estimated values by Uber.

Ride request time refers to the specific time that a user, or this case, computer, requests a ride. Because the study periods bridged days from 10:00 pm to 2:30 am, ride request time was input as the proportion of the day, where the 24-hour clock is represented on a scale of 0 to 1. In order to indicate a time of 12:00 am to 2:30 am as continuous along the study period, a one was added to those early morning hours. As such, ride request times in the study ranged from 0.918 to 1.104.

5. Results

Descriptive statistics indicate that the majority of all ride requests during the study periods did not have surge pricing. The median surge price multiplier for all three study dates remained at 1, as did the mode, indicating that for most of the study period, a rider would not have been subjected to surge pricing. However, the maximum surge price for the July 4, 2015 study period reached a maximum of 6.1, which exceeded the July 3, 2015 maximum by 3.3 and the July 5, 2015 maximum by 4. In addition, the mean surge price for July 4, 2015 was 26.06% greater than the mean surge price for July 3, 2015 and 29.39% greater than the mean surge price for July 5, 2015. The standard

Table 1
Descriptive statistics of surge pricing during the July 4th weekend, 2015.

Date	July 3, 2015	July 4, 2015	July 5, 2015
Start time	7/3/15 22:00	7/4/15 22:02	7/5/15 23:54
End time	7/4/2015 0:44	7/5/2015 2:14	7/6/2015 2:29
Surge price mean	1.04	1.31	1.01
Surge price median	1	1	1
Surge price mode	1	1	1
Surge price standard deviation	0.17	0.77	0.09
Surge price minimum	1	1	1
Surge price maximum	2.8	6.1	2.1
Count of data points	3330	4160	2981

Table 2
Descriptive statistics of pick-up and wait time during the July 4th weekend, 2015.

Descriptive statistics, pick-up wait time			
Date	July 3, 2015	July 4, 2015	July 5, 2015
Start time	7/3/15 22:00	7/4/15 22:02	7/5/15 23:54
End time	7/4/2015 0:44	7/5/2015 2:14	7/6/2015 2:29
Pick-up time mean	445.8	444.0	505.5
Pick-up time median	408	401.5	444
Pick-up time mode	357	261	422
Pick-up time standard deviation	244.4	258.3	277.4
Pick-up time minimum	35	31	21
Pick-up time maximum	2229	3284	2453
Count of data points	3330	4160	2981

deviation of price surge points for the July 4 study period reached 0.7673, while the standard deviation of price surge points for July 3, 2015 was 0.1729 and the standard deviation of price points for July 5, 2015 was 0.0928 (Tables 1–3).

Descriptive statistics for the pick-up wait time were generated in order to ascertain general characteristics about one of the variables explored in the regression models. With this set of data, the mean wait time in seconds for the July 3, 2015 and the July 4, 2015 study period only varied by 1.86 s. The mean wait time for July 5, 2015 was about 1 min longer than July 3, 2014 and July 4, 2015. The median wait times for July 3, 2015 and July 4, 2015 were also more alike and shorter than that of July 5, 2015, with the earlier days' median wait time clocking in at 36 and 42.5 s less than July 5, 2015's value respectively. However, the range of estimated wait times for July 4, 2015 was much longer than the other two study periods. The maximum pick-up wait time for the Fourth of July holiday reached 3284 s, or 54.73 min. The maximum wait time for July 3, 2015 was 2229 s (37.15 min) and the maximum wait time for July 5, 2015 was 2453 s (40.88 min).

Two simple linear regression models were run on the three study periods, resulting in six total regression analyses. Of those, none of the models meant to predict surge price multiplier by ride wait time were statistically significant. In addition, the models predicting surge price multipliers by ride request time were statistically significant in those three days, however July 3 and July 5 had a very low adjust R square. For July 4, 2015, a significant regression equation was found with a strong adjusted R^2 of 0.219. The predicted surge multiplier is equal to 1.01 plus 0.84 times ride request time measured as a ratio of the 24-hour clock as described above. This suggested that ride request time had a strong impact on price surge multiplier in July 4. The author also did separated tests to see if there was any significant correlation between ride request time and price surge. A stronger correlation was also found in July 4, 2015 (results not shown).

6. Limitations

The most significant limitation was the errors in computer recording of data points. This made it difficult to make a true comparison between the three study days. In addition, the restrictions on data as designed by Uber in the development of its API provided challenges for researchers. Although the surge price mechanism is an item designed and deployed by Uber engineers, this algorithm in not shared. Attempting to piece this function together through hypothetically generated trip data that does not provide information such as number of total rides requested, among other items, limits the potential understanding that can occur through Uber data analysis. Though this particular study merely scratched the surface of the insight and capabilities of data gleaned from sources like Uber, it does provide considerable insight into how the technology functions and what subsequent studies might uncover through this powerful data. Future research should incorporate survey data in order to narrow the geographic boundaries to specific study areas and identify the most meaningful times to investigate. With a narrowed scope, more in-depth research could occur on the specific mechanisms behind surge pricing in relation to location and time.

7. Discussions

The descriptive statistics of surge pricing indicate that the values of surge price multipliers during the Fourth of July holiday evening were greater and more varied than those on July 3 and July 5, 2015. This is supported by increased surge price mean over the other study days, as well as the greater standard deviation, which indicates that the surge prices were less clustered. GIS visualization of ride requests with surge points distributed by day and magnitude across the City of Austin lends a graphic representation of this phenomenon, wherein surge multipliers on July 4, 2015 are clearly greater in magnitude and frequency. This GIS representation also indicates that Uber surge pricing primarily affects areas within the core highway loop of the City of Austin. Although data points were gathered in a 12.5 by 12.5 mile square around the city, surge prices were nearly all southwest of US 183, north of TX 71, and east of TX 360.

Overall, the results of the analysis indicate that Uber surge pricing escalates during special events. However, the lack of significance found in simple regression models reveals the opacity of Uber's surge pricing. Estimated ride wait time may not be significant because of the distance from a driver, not because there are not enough drivers or too high of a demand at the time of the ride request. Ride request time may not be significant unless a multitude of users request a ride at the same time, triggering a quick influx of demand that the working drivers cannot immediately satisfy. However, Uber does not provide the number of

Table 3
Regression results of the pricing surging analysis (*Bold and Italic*: Significant at 0.01).

Predictor variable	Study period	n	Intercept	Coefficient (B)	t	p	Adj. R^2
Pick-up wait time	July 3, 2015	3330	1.04	0.00	−0.79	0.42	−0.000
Pick-up wait time	July 4, 2015	4160	1.35	0.00	−2.31	0.02	0.001
Pick-up wait time	July 5, 2015	2981	1.01	0.00	1.18	0.20	0.000
Ride Request Time	***July 3, 2015***	***3330***	***1.00***	***0.05***	***7.49***	***0.00***	***0.016***
Ride Request Time	***July 4, 2015***	***4160***	***1.01***	***0.84***	***34.12***	***0.00***	***0.219***
Ride Request Time	***July 5, 2015***	***2981***	***1.01***	***0.03***	***2.89***	***0.00***	***0.002***

ride requests made through its API. This data omission may be a significant barrier to understanding how price surges work. Thus, in order to better incorporate Uber and other TNCs into the existing urban transportation system, they should be required to provide more information about the price surge factors and the requested and actual rides to urban planners and policy makers.

This study did provide valuable insight into the potential magnitude of surge pricing. Collected data shows that the price surges can produce a ride cost that is 6.1 times a non-surge rate, which may make the service prohibitively expensive to some citizens during peak times. For example a ride priced $25 during a non-surge pricing time would cost $152.50 when confronted with a 6.1 surge price multiplier. The affordability matter becomes more urgent when considering that surge pricing cannot be easily predicted by time of ride request and geography, which are the two items furnished by Uber's API that are also evident to potential riders. Although Uber does provide a price estimate to users before asking for ride confirmation, the unpredictability of the service's pricing is relevant to planners working on transportation accessibility, in particular. Future research should focus on the potential for these services to replace public transportation trips and/or reduce the demand for public transportation among those riders who can afford rideshare services. The significance of the potential reduced demand and for public transportation becomes more pronounced when considering the impact for transit riders who do not have the resources to rely on TNCs. A parallel study in New York City showed that TNCs could not fill the transit demand and supply gap (transit desert) in low income neighborhoods, as TNC trips were naturally pulled towards high income neighborhoods due to affordability reasons. The pattern was more obvious in busy hours considering the impact of price surge. (This study is currently under review for publication elsewhere). Thus how to maintain and coordinate TNCs and public transits within cities and provide enough transit services for low-income bracket has become an important equality question.

Beyond the surge information gleaned from the API, the process of gathering and analyzing data to understand and predict surge prices creates a burden for transportation planners. Planners are implicated by Uber's operations, which purport to "[fill] the gaps left by traditional transportation options" (Graves, 2014). This barrier to information may provide additional arguments against rideshare services on behalf of cities and regulatory bodies, who are tasked with understanding the transportation landscape in order plan for operations, efficiency, and access. Currently, the burden of understanding how this pricing works is left to the individual and the transportation planner. The variable, market-based pricing of TNC services may pose transportation access and equity issues if planners are not provided with adequate information as to their functionality.

For transportation managers who are seeking to utilize TNC services like Uber as a complementary service alongside traditional transportation systems, understanding Uber's pricing strategy is critical. Getting pricing right and avoiding envelopment are the utmost priorities in the winner-take-all environment of these new transportation services (Heiskala et al., 2016). This is especially true given inevitable changes that may affect Uber and other TNCs profit margins. Legally, Uber, Lyft, and other TNCs have been to classify themselves as a ride "matchmaking" service, as opposed to a transportation service (Dobson, 2015). As such, they hire drivers as "individual contractors" who work whatever hours they choose rather than employees, which dramatically drives down their costs (Dobson, 2015; Redfearn, 2016). The fact that drivers choose when they work and provide their own vehicle is also the main impetus for the surge pricing multiplier. Drivers (and their personal vehicles) must be enticed into providing services through the higher pay that comes with surge pricing. If regulatory frameworks change and TNCs are no longer able to rely on "independent contractors" but must instead hire their own employees, will this be the end of surge pricing? Or will surge pricing algorithms change to ensure that supply and demand stay balanced and the business stays viable?

And as technology continues to evolve, the proliferation of shared automated vehicles (SAVs) will affect Uber's surge pricing strategy as well. As vehicles become driver-less, how will the market respond? Currently, TNC services rely on the vehicles owned by individual drivers. However, the advent of SAVs may require that these companies own their automated fleet, more in line with the traditional transportation company model. In the future, "who owns the vehicle(s) and who controls the SAV network operational decisions become the two most important factors when defining SAV business models" (Stocker & Shaheen, 2016). Surge pricing will need to adapt, as the current algorithm will no longer be relevant for controlling supply and may, instead, turn away large numbers of potential customers. Understanding Uber's pricing strategy now will help transportation managers, policy makers, urban planners adapt it for future use.

Acknowledgements

The author would like to thank Rahul Gupta, Susan Sharp, and Nicole McGrath for their contributions in data collection and analysis. This study was supported in part by the Cooperative Mobility for Competitive Megaregions University Transportation Center through the United States Department of Transportation.

References

Anderson, D. N. (2014). "Not just a taxi"? For-profit ridesharing, driver strategies, and VMT. *Transportation, 41*(5), 1099–1117.

Bercovici, J. (2014). Uber director defends surge pricing as SXSW riders lament it. Forbes. Retrieved from: http://www.forbes.com/sites/jeffbercovici/2014/03/11/uber-director-defends-surge-pricing-as-sxsw-riders-lament-it/, Accessed date: 7 July 2017.

Casabien, E. (2012). Hurricane Sandy/pricing update. Uber newsroom. Retrieved from: http://newsroom.uber.com/nyc/2012/11/hurricane-sandy-pricing-update/, Accessed date: 7 July 2017.

Chen, L., Mislove, A., & Wilson, C. (2015). Peeking beneath the hood of Uber. *2015 ACM Conference on Internet Measurement Conference* (pp. 495–508). .

Chen, M. K., & Sheldon, M. (2016). *Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform* (Working Paper)Los Angeles: University of California1–19.

City of Austin (2017). Austin City Code—Chapter 13-2. Ground transportation passenger services. Retrieved from: https://lintvkxan.files.wordpress.com/2013/11/austin-city-code-13-2-updated.pdf, Accessed date: 7 July 2017.

Cohen, B., & Kietzmann, J. (2014). Ride on! Mobility business models for the sharing economy. *Organization & Environment, 27*(3), 279–296.

Crampton, J. W., Graham, M., Poorthuis, A., Shelton, T., Stephens, M., Wilson, M. W., & Zook, M. (2013). Beyond the geotag: Situating 'big data' and leveraging the potential of the geoweb. *Cartography and Geographic Information Science, 40*(2), 130–139.

Currie, G. V. (1997). The planning and performance of mass transit operating strategies for major events: The Atlanta Olympic Games and the 1996 Melbourne Formula 1 Grand Prix. *Australian Institute of Traffic Planning and Management (AITPM) National Conference* (pp. 79–91). .

Dailey, D. J., Loseff, D., & Meyers, D. (1999). Seattle smart traveler: Dynamic ridematching on the world wide web. *Transportation Research Part C: Emerging Technologies, 7*(1), 17–32.

Daus, M. W. (2013). *Ridesharing applications: Illegal "hitchiking-for-hire" or sustainable group riding? A legal and policy primer for ground transportation regulation.* New York: Windels Marx Lane & Mittendorf, LLP.

Diakopoulos, N. (2014, April 17). How Uber surge pricing really works. Washington Post. Retrieved from: http://www.washingtonpost.com/news/wonkblog/wp/2015/04/17/how-uber-surge-pricing-really-works/, Accessed date: 10 July 2015.

Dobson, E. (2015). Transportation network companies: How should South Carolina adjust its regulatory framework. *South Carolina Law Review, 66*(4), 701–725.

Firnkorn, J., & Müller, M. (2011). What will be the environmental effects of new free-floating car-sharing systems? The case of car2go in Ulm. *Ecological Economics, 70*(8), 1519–1528.

Frantzeskakis, J. M. (2006). *Athens 2004 Olympic games: Transportation planning, simulation and traffic management. 76(10)*, Institute of Transportation Engineers26.

Global e-Sustainability Initiative (2008). *SMART 2020: Enabling the low carbon economy in the information age (United States report addendum).* (Prepared by Boston Consulting Group for GeSI).

Golob, J., & Giuliano, G. (1996). Smart traveler automated ridematching service lessons learned for future ATIS initiatives. *Transportation Research Record, 1537*, 23–29.

Graves, R. (2014). Providing rides when they are most needed. Uber Newsroom. Retrieved from: http://newsroom.uber.com/austin/2014/09/providing-rides-when-they-are-most-needed/, Accessed date: 1 August 2015.

Gurley, B. (2014). A deeper look at Uber's dynamic pricing model. Above the Crowd. Retrieved from: http://abovethecrowd.com/2014/03/11/a-deeper-look-at-ubers-dynamic-pricing-model/, Accessed date: 9 September 2017.

Heiskala, M., Jokinen, J. P., & Tinnilä, M. (2016). Crowdsensing-based transportation services—An analysis from business model and sustainability viewpoints. *Transportation Business & Management, 18*, 38–48.

Hicks, N., & Wear, B. (2016, May 09). City hall grapples with Uber, Lyft departure as new firms eye opening Austin-American Statesman. http://www.mystatesman.com/news/local/city-hall-grapples-with-uber-lyft-departure-new-firms-eye-opening/zY4fV9zVSWeg9IAlbPIPYJ/.

De Jong, M., & van Dijk, M. (2015). Disrupting beliefs: A new approach to business-model innovation. *The McKinsey Quarterly, 3*, 66–75.

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with machines: The impact of algorithmic and data-driven management on human workers. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 1603–1612). .

Martin, E., Shaheen, S., & Lidicker, J. (2010). Impact of carsharing on household vehicle holdings: Results from North American shared-use vehicle survey. *Transportation Research Record, 2143*, 150–158.

Martin, E. W., & Shaheen, S. (2011). Greenhouse gas emission impacts of carsharing in North America. *IEEE Transactions on Intelligent Transportation Systems, 12*(4), 1074–1086.

Miller, S. R. (2016). First principles for regulating the sharing economy. *Harvard Journal on Legislation, 53*, 149–172.

Morency, C. (2007). The ambivalence of ridesharing. *Transportation, 34*(2), 239–253.

Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy, 45*, 168–178. http://dx.doi.org/10.1016/j.tranpol.2015.10.004.

Redfearn, R. L., III (2016). Sharing economy misclassification: Employees and independent contractors in transportation network companies. *Berkeley Technology Law Journal, 31*(2), 1023–1056.

Robbins, D., Dickinson, J., & Calver, S. (2007). Planning transport for special events: A conceptual framework and future agenda for research. *International Journal of Tourism Research, 9*(5), 303–314.

Roche, M. (1994). Mega-events and urban policy. *Annals of Tourism Research, 21*(1), 1–19.

Shelton, T., Poorthuis, A., & Zook, M. (2015). Social media and the city: Rethinking urban socio-spatial inequality using user-generated geographic information. *Landscape and Urban Planning, 142*, 198–211.

Stocker, A., & Shaheen, S. (2016). Shared automated vehicles: Review of business models. *Discussion paper: International transport forum* (pp. 1–28). . Retrieved from: http://www.itf-oecd.org/sites/default/files/docs/shared-automated-vehicles-business-models-review.pdf.

Strong, K. C. (2015). When apps pollute: Regulating transportation network companies to maximize environmental benefits. *University Of Colorado Law Review, 86*, 1049–1095.

Uber (2015). What is surge pricing? Retrieved from: https://help.uber.com/h/6c8065cf-5535-4a8b-9940-d292ffdce119, Accessed date: 14 August 2015.

Vogel, P., Greiser, T., & Mattfeld, D. C. (2011). Understanding bike-sharing systems using data mining: Exploring activity patterns. *Procedia - Social and Behavioral Sciences, 20*, 514–523.

Wear, B. (2013, March 23). *Uber, Lyft and how to barge in.* Austin American-StatesmanB1.

Wear, B. (2014a). *Uber driving around detours.* Austin American-StatesmanB1.

Wear, B. (2014b). *An Uber important year for commuters.* Austin American-StatesmanB1.

Wear, B. (2015a). *Uber, Lyft sign six-month deal with Austin for airport.* Austin American-StatesmanB5.

Wear, B. (2015b). *Uber, Lyft cut deal for airport.* Austin American-StatesmanB1.

Wear, B. (2017, May 29). *Lyft and Uber return to Austin as Abbott signs ride-hailing bill.* Austin American-Statesman. Retrieved from: http://www.mystatesman.com/news/state–regional-govt–politics/lyft-and-uber-return-austin-abbott-signs-ride-hailing-bill/Pa0AGqaHINipIUEme9MFfM/.