The Limitations on Uber's Ability to Eliminate Market Inefficiencies

By: Nicolas Barker
Advisor: Professor Christopher Maxwell
Boston College Economics Department
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1. INTRODUCTION:

A market's efficiency is determined by the degree to which pertinent information is available to both consumers and suppliers and how quickly prices can respond accordingly to shifts in demand and supply. The proliferation of mobile technologies has facilitated the distribution of this information, as well as payment capabilities, to both consumers and suppliers of many services. A new type of economy, the "sharing economy", has emerged as a result of digital platforms that position themselves as intermediaries between consumer demand and supply. Because these digital platforms are often in the form of mobile applications on smartphones, new technology companies have leveraged the potential of millions of consumers and suppliers. Uber Technologies Inc. is a technology company with a "ride-sharing" digital platform, "Uber", that matches for-hire drivers with riders.

Uber charges the rider a base fare that is calculated according to certain fixed fees, a mileage rate, and a duration rate. This base fare is meant to both be an attractive alternative to riders compared to other traditional "for-hire" transportation options as well as attract enough driver supply to meet demand during normal market conditions. In times of heightened demand, Uber implements a dynamic pricing model called "surge pricing" that acts as a base fare multiplier. Uber claims that its surge pricing benefits the riders because it attracts drives to the areas with increased demand due to higher fares for the drivers. However, dynamic pricing in the ride-hailing industry is revolutionary compared to the traditional fixed-rates and fees by city taxi fleets. This has caused for much tension between Uber and regulators as well as riders who are not accustomed to the new business practices.

This paper focuses on Uber's ride-sharing platform and surge pricing practices and their impact on the efficiency of the ride-hailing market by both reviewing previous research on the topic and developing several new data sets. An elasticity model is derived from real-time data that (1) demonstrates that the Uber platform and its use of surge pricing increases the efficiency of the ride-hailing market and (2) identifies remaining inefficiencies, especially over the short term, due to certain specific factors in both the ride-hailing market and how Uber manages pricing and information distribution.

2. BACKGROUND:

Uber Technologies Inc. was founded on March 1st, 2009 in San Francisco as a mobile application to request for-hire luxury black cars in a handful of metropolitan areas. It has since expanded its offerings to include economy transportation, luxury transportation, and delivery services all around the world[1]. Uber is currently number one in the US ride-hailing industry, owning an estimated 80% market share. It was valued most recently at $68 billion, with $18 billion raised in debt and equity. This valuation is more than nine times the valuation of their closest competitor, Lyft [2]. Uber's progress can be seen in the growth rate of total number of rides around the world. It took approximately five and a half years (March 2009 – December 2015) for Uber to obtain its first 1 billion rides, compared to only six months to obtain its second billion total rides (December 2015 – July 2016).

2.1 Rider and Driver Experience:

The Uber platform facilitates a trilateral relationship between the digital application, the drivers, and the riders. The riders interact with Uber using the "Uber Rider Application." Riders use the app to view ride wait times and fare estimates, submit requests, and pay their fares. By channeling all platform interactions through the mobile app, Uber is able to monitor all traffic and user interactions whether or not the consumer's experience ultimately culminates in submitting a ride request. Furthermore, Uber is also able to gather supplemental background information on the user's smartphone that is pertinent to the transaction such as passenger location before and after a completed ride as a means to improve passenger pick-up and drop-off experience.[3]

Drivers communicate with Uber using the "Driver-Partner Application", which enables drivers to see fares and rates set by Uber (including surge factors), accept rider requests, and be compensated. [4] Drivers of these private cars make themselves available for-hire by going "online" through the driver app. Uber drivers

[1] Economy transportation services (UberPOOL, UberX, and UberXL) differ from the luxury transportation services (UberBLACK and UberSUV) in that the luxury servicers are Transportation Charter Permit licensed and the vehicles must meet higher standards.
[2] "From Zero to Seventy; Uber" (The Economist, 2016)
[3] Conger, Kate (TechCrunch, 2016).
[4] The difference between the rider and driver apps can be seen in Figure 1 in the Appendix.

are not able to see the destination of the rider until passenger pick-up in order to prevent drivers from favoring riders requesting long, and thus more lucrative, trips over those with shorter ride requests. It is important to note that drivers are hired by Uber as private contractors and thus the drivers decide where, when, and how long they ultimately work. The only direct interaction between the drivers and riders occurs during the passenger's ride from pick-up to destination.

Uber's innovative rider and driver experience has revolutionized the transportation industry and especially the taxi and limousine industry. Consumers are no longer willing to accept the unpredictable availability and wait time of either trying to hail or call a taxi during peak hours or (in large urban markets) calling a traditional car service which requires that consumers pay in advance. Consumer experience for any ride-hailing service, whether that for be traditional metered taxis or for new services such as Uber or Lyft, is comprised of three major factors:

- The origin and destination (OD) pair requested by the rider
- The fare for transportation from the origin to destination
- Number of drivers, driver availability, and proximity to passenger's pick-up location, and resulting driver estimated time of arrival (ETA)

The fare and driver availability are controlled by the ride-hailing services while the OD pair is set by the passenger. With the OD pair set by the passenger, either only the fare or driver availability can be prioritized. Traditionally, metered taxis have been highly regulated in terms of in the number of available licenses and the fixed fare structure they were allowed to charge. As a result of fixed taxi supply and pricing, this often produced taxi shortages during times of high demand. Uber's consumer service, however, prioritizes consistent availability and ETA at the passenger's pick-up location rather than a consistent fare structure. Uber's consistent driver availability requires its dynamic pricing model called "surge pricing".

2.2 Surge Pricing:

Uber implements a dynamic pricing model called "Surge Pricing" in order to attempt to equilibrate short-term levels of supply and demand during times of shifting market conditions [8]. Uber sets the value of the fare components, including booking and service fees, mileage rates, and minute rates, in order to calculate a base fare. A surge factor is a multiplier that increases this base fare during times of heightened demand[5]. The value of the surge factor is calculated in real time by an automatic algorithm according to market conditions. Uber claims that such dynamic pricing is beneficial for both riders and drivers.

> "During times of high demand for rides, fares may increase to make sure those who need a ride can get one. For riders, surge helps ensure that pickup is available quickly and reliably. For driver-partners, surge means higher fares and a steady stream of ride requests."
>
> – Uber Help Website (help.uber.com)

Uber's surge pricing generates criticism for several reasons, including the accusation that it is a form of price gouging during times of inelastic demand. Consumers often have a preconceived notion of the "normal" or "fair" cost for a given trip, and even if they acknowledge the demand-supply imbalance and are unwilling to wait longer for alternative transportation, they will nonetheless feel exploited by Uber's surge

[5] An in-depth analysis of the fare breakdown occurs later on in the paper.

pricing. The following are few customer reactions to Uber's surge pricing during a BART outage in San Francisco on Monday March 27th, 2017.[6]

Surge pricing is calculated automatically by the Uber demand-supply algorithm; there is no real-time monitoring by Uber to confirm the appropriateness, effectiveness, or acceptability of the surge factor. This has led to situations where the surge factor rises and falls automatically and rapidly, without examination of the underlying cause for the demand surge or supply drop. Especially in the event of widespread civil emergencies, spikes in surge pricing are considered unethical and even dangerous (see next section).

In addition, others criticize how surge is integrated into fare pricing. Surge factors are calculated to an arbitrary number of decimal points by the algorithm but charged to the rider as a rounded multiplier. In other words, this may lead to one person paying 1.4X for the base fare for a 1.449 surge factor versus another rider paying 1.5X the base fare for a surge factor calculated at 1.451. The difference in market conditions between a calculated surge factor of 1.449 and 1.451 are negligible but result in paying an additional 7%. Furthermore, surge factors are specific to pre-defined geographical areas. Thus, this may lead to times where simply crossing the street in order to enter a different geographical area results in a lower surge factor.

In addition, because the surge multiplier is calculated automatically in real time using a proprietary algorithm, there can sometimes be lags in the calculations of fare multipliers with respect to changes in supply and demand. This can occur in the beginning of a surge period when the demand has already increased yet there is still no surge multiplier because current levels of supply are being depleted or at the end of a surge

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[6] Zimmerman, Douglas (SF Gate, 2017).

period resulting in abnormally high prices for areas that have returned to standard levels of demand. These inefficiencies of surge pricing will be highlighted in the discussion of the derived elasticity model later in this paper. Many of these criticisms have come from their users who have shared their stories through the media.

2.3 Uber in the News:

There have been multiple instances where Uber has been accused of unethical price gouging as a result of allowing the surge price algorithm to escalate automatically to what is perceived as an excessive level during inappropriate times. During the Sydney hostage crisis in 2014, the surge multiplier peaked at 4.0X the base fare as a result of panicked people trying to leave the area for their physical safety [6]. While this was not Uber's intentions, it caused a public outrage as Uber was accused of exploiting its customers during a time of public crisis. Uber quickly apologized and refunded rides, but the incident damaged Uber's reputation. Uber was also criticized for allowing surge pricing to reach extreme levels during Hurricane Sandy in 2012. As people rushed home during the inclement weather, Uber tried to incentivize drivers by implementing surge pricing. Again, this caused a public outcry as people accused Uber of taking advantage of its customers. In response, Uber charged the riders the normal base fare with no surge multiplier but continued to pay the drivers 2X the base fare [6]. This cost Uber $100,000 per day until they returned the rider's fare to be equal to the surge multiplier.

These events occurred due to Uber's automatic calculations of surge factors in real time. While this pricing algorithm does enable Uber to adapt to rapidly changing market conditions, it can result in unintended consequences that threaten Uber's reputation. Whether surge pricing is ethical or not, it is definitely consumers' and regulators' biggest criticism of the Uber platform.

3. LITERATURE REVIEW:

Four scholarly articles were most useful in developing this paper's methodology and analysis:

1. *"The Effects of Uber's Surge Pricing: A Case Study"*, by Hall et al. (Uber, 2015).
2. *"Peeking Beneath the Hood of Uber",* by L. Chen et al. (Northeastern University, 2015).

3. *"Using Big Data to Estimate Consumer Surplus: The Case of Uber"*, by Cohen et al. (National Bureau of Economic Research, 2016).

4. "*Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform"*, by M. Keith Chen and Michael Sheldon (UCLA and U. of Chicago, 2015).

"The Effects of Uber's Surge Pricing: A Case Study" provided specific insight into Uber's justification of surge pricing. *"Peeking Beneath the Hood of Uber"* was extremely helpful in developing a methodology and structure an analysis of Uber's pricing model. *"Using Big Data to Estimate Consumer Surplus: The Case of Uber"* identify further research opportunities and analysis in the derivation of supply and demand elasticity. The fourth piece discussed in this section, "*Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform",* offered complementary context that helped explain certain phenomena in rider and driver experiences and prompted questions to investigate.

3.1 *"The Effects of Uber's Surge Pricing: A Case Study"* By: Jonathan Hall, Cory Kendrick, and Chris Nosko (Uber Technologies), 2015.

In response to public criticism of Uber's practice of surge pricing, Hall, Kendrick, and Nosko wrote a case study, "*The Effects of Uber's Surge Pricing: A Case Study"*, explaining how Uber's surge pricing helps equilibrate consumer demand and driver supply when the two are not at equilibrium.[7] This analysis was able to leverage in-house data proprietary to Uber. This was an enormous advantage because Hall et al. had access to precise rider demand and driver supply data that are not available to drivers, riders, or researchers. In addition, they were able to gain insight into the different types of demand that help explain the effectiveness of surge pricing. They were able to distinguish between users who have only opened the app, from those who have requested a ride but are still waiting to be picked up, from those who have actually been serviced. It was important to categorize demand into these three types because each one explains different metrics used in surge pricing calculations. Those who open the application but do not request any Uber product could

[7] Jonathan Hall is currently the Head of Economic Research, Legal and Public Policy at Uber Technologies Inc. with a PhD in Economics from Harvard University. Cory Kendrick is a Data Scientist at Uber Technologies with a BA in Cognitive Science from Dartmouth College. Chris Nosko is a professor at the Booth School of Business at the University of Chicago with a PhD in Economics from Harvard University.

represent those deterred by the surge multiplier. Those who have requested a ride but are still waiting to be picked up provide insight into pick up waiting times, which is a critical benchmark by which surge price effectiveness is evaluated. Finally, those who have already been serviced provide insight into the rider's satisfaction with the price he paid for the driver ETA and completed trip.

Their case study focused on two events in order to highlight the effect of surge pricing on rider demand and driver supply. First, they analyzed a sold-out concert at Madison Square Garden in New York City by pop sensation Ariana Grande, where surge pricing successfully handled spikes in local passenger demand at the end of the concert. The second event was New Year's in New York City in 2015, when the surge multiplier broke down due to a technical malfunction in the algorithm and allowed supply and demand to remain in disequilibrium for an extended period.

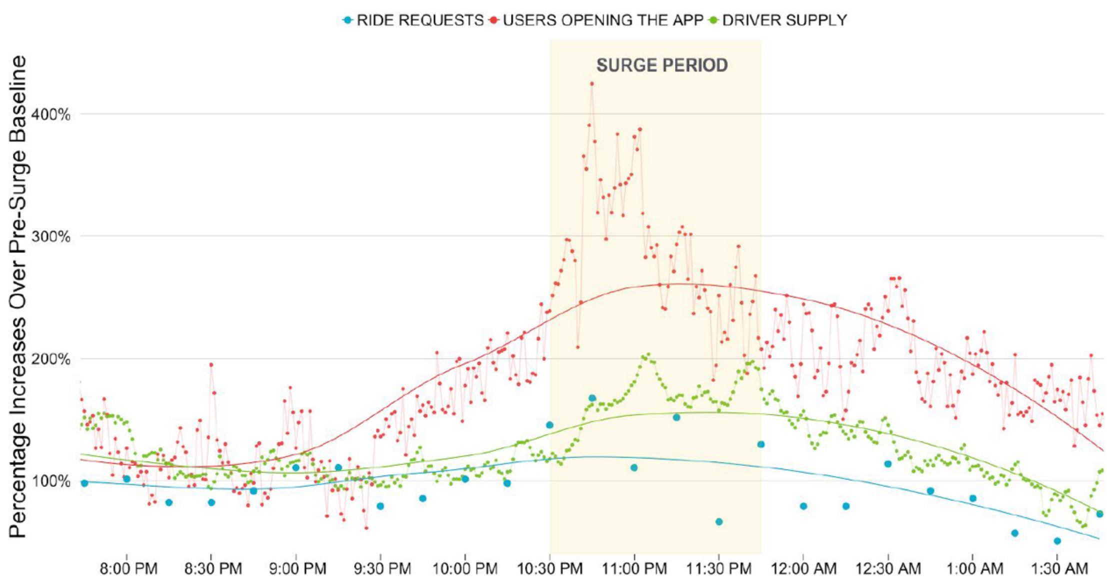

Figure 1: Levels of supply and demand at the end of the sold out Ariana Grande concert at Madison Square Garden on March 21nd, 2015 in New York City

Ariana Grande Concert, Madison Square Garden, New York City, 3/21/2015:

During the Ariana Grande concert, the authors were able to track levels of supply and demand before, during, and at the end of the concert. Figure 1, the level of rides demanded increased towards the end of the concert as people left the concert and was followed by a subsequent increase in driver supply. While there was an obvious correlation between the increase in rider demand and the trailing increase in driver supply during the surge period, Hall et al. admitted that it was difficult to determine how much of this relationship was causal versus correlative (p. 3). This ambiguity results from the inability to attribute the increase in supply to real-time surge pricing or driver personal interest to take advantage of an anticipated increase in demand. According to Hall et al., the most effective metrics for measuring the effectiveness of surge pricing, whether it be correlative or causal, were the completion rate and driver ETAs for rides during the surge period.

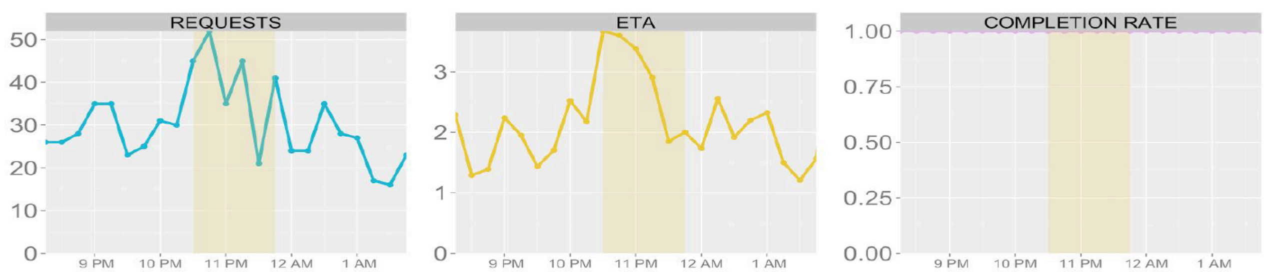

Figure 2a: Critical metrics for the Ariana Grande concert at Madison Square Garden on March 21nd, 2015 in NYC

In the example of the Ariana Grande concert, the completion rate was maintained at 100% and the driver ETA reached a maximum of just over 3.5 minutes with the surge multiplier reaching its peak of 1.8X (p. 5). In comparison, the 2015 New Years Eve example depicted what happened to these metrics when surge multipliers did not equilibrate supply and demand.

New Year's Eve, 1/1/2015:

In the first hours of the New Year in 2015, the surge pricing algorithm broke down from 1:24AM to 1:50AM due to technical malfunctions. Before the surge pricing outage, the surge multiplier was at 2.7X, which was indicative of a preexisting disequilibrium between supply and demand. As a result, the same metrics, completion rate and driver ETA, suffered dramatically. At its worst, the completion rate fell to below 25% while driver ETA sky rocketed to nearly 8 minutes.

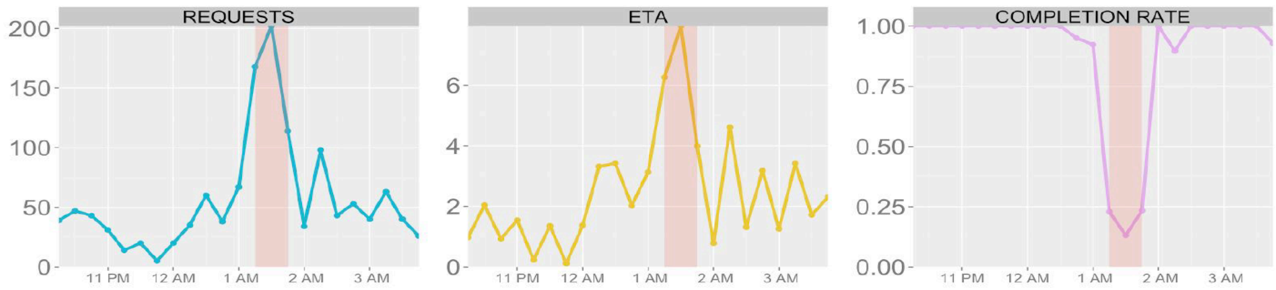

Figure 2b: Critical metrics for the 2015 New Year's surge pricing outage in NYC

While this case study is unique in that it had unprecedented access to aggregate data that enabled a more precise analysis of the effectiveness of surge pricing, it suggested that surge pricing had at least a strong correlative relationship with equilibrating driver supply with passenger demand and maintaining a 100% ride completion rate. This analysis is critical to evaluating the effectiveness of surge pricing because it was the most precise analysis based on near-perfect, insider data. That said, it is still important to note that in both cases (correct surge pricing and malfunctioning surge periods), Uber was unable to maintain driver ETA at a consistent level at all times, which implies that there are still inefficiencies in Uber's dynamic pricing model.

3.2 ***"Peeking Underneath the Hood of Uber"* By: Le Chen, Alan Mislove, and Christo Wilson (Northeastern University), 2015.**

In *"Peeking Underneath the Hood of Uber",* a group of computer scientist, Chen, Mislove and Wilson from Northeastern University, provided an in-depth analysis of the different components of Uber's surge pricing algorithm in an attempt to evaluate its impact on levels of driver supply and passenger demand in a geographically defined market area.[8] Chen et al. stated that the original purpose for their work was to shed light on the controversial "black-box" that Uber has created through their protection of proprietary data (p. 1). Uber does not share publicly any data on its levels of aggregate supply and demand compared to other open marketplace companies such as AirBnB, which shares all available listings and their prices at all times.

[8] Le Chen is a PhD candidate and Research Assistant at Northeastern University with a BE in Information Engineering from the Beijing University of Posts and Telecommunications. Alan Mislove is a Computer Science Associate Professor at Northeastern University with a PhD in Computer Science from Rice University. Christo Wilson is an Assistant Professor of Computer Science and Information Science at Northeastern University with a PhD in Computer Science from University of California, Santa Barbra.

In addition, Uber, unlike many sharing platforms, determines prices itself rather than allowing suppliers to set their own prices.

Chen et al. created their own real time dataset by leveraging Uber's API (Application Program Interface) in order to gather fare estimates on simulated ride requests in both Manhattan and San Francisco over two two-week intervals in April and May of 2015.[9] They integrated 43 unique fictitious Uber accounts with their custom-built program whose functionality replicated that of the Uber rider application. This allowed them to simulate requests from all of their 43 accounts in a certain geographically defined area.

(a) Uber in downtown SF. (b) Uber in midtown Manhattan. (c) Taxis in midtown Manhattan.

Figure 3: The location and positioning of the fictitious Uber accounts by Chen et al.

Because of Uber's protection of proprietary data, Chen et al. created their own proxies for supply and demand. Their supply proxy was the number of *unique* car IDs seen across the 43 different accounts during a certain time interval *t*. This approach was used because Uber only provides the 8 closest drivers to any individual client looking to request a ride (p. 3). Thus, the authors strategically placed all 43 of their fictitious clients in order to ensure "blanket" coverage of a certain geographically defined market area. They followed a similar method for developing their proxy for demand by recording the number of drivers that they saw "disappear" from the area over a certain period of time across the 43 accounts. However, it is important to note that this is *fulfilled* demand rather than *ride-request* demand.[10] This difference was due to Uber's lack of

[9] Using a company's API allows the user to replicate a certain level of the company's application functionality in a third-party environment. Companies develop an API in order to encourage the use of their services by third party developers. In this example, Chen et al. were able to develop their own program that retrieved real time Uber fare requests directly from the Uber servers.

[10] This implies that they were unable to capture the customers who requested a ride and never got served or those who opened the application and never actually requested a ride for any reason.

transparency regarding different types of demand as previously described. Finally, this proxy for demand established an upper bound on *fulfilled* demand, as they were unable to distinguish cars that disappeared due to picking up passengers from cars that went offline.

The results that their analysis yielded were inconclusive regarding any clear relationship between surge price multipliers and levels of supply and demand as well as driver ETA. In evaluating surge pricing's ability to adapt supply to changing market conditions, Chen et al. treated each driver as a state machine to predict future driver behavior depending on local and surrounding surge factors. Drivers were able to be in one of five states consisting of *"new", "old", "in", "out",* or *"dying"*.[11]

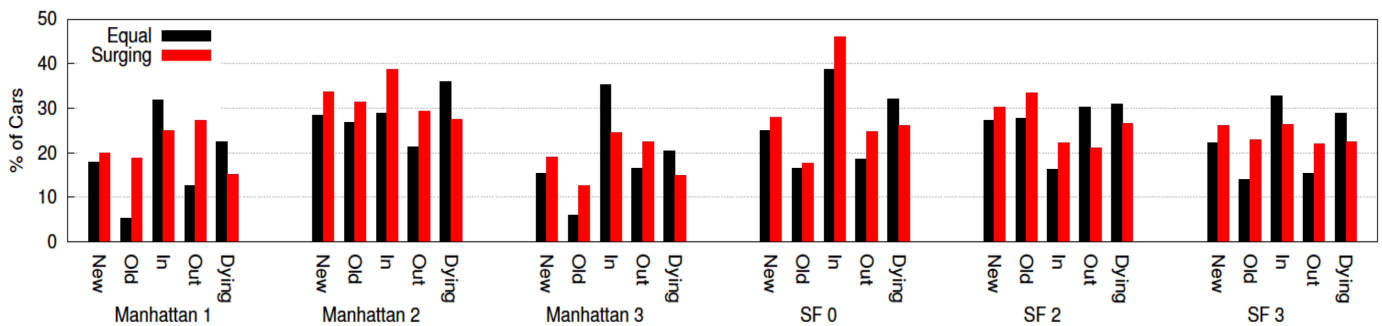

Figure 4: Driver state-machine transition probabilities for six different adjacent areas during times of equal surge versus unequal surge.

In Figure 4, state-transition probabilities for drivers in two sets of different adjacent geo-market areas, Manhattan 0, 1, 2 and San Francisco 0, 1, 2, were compared between times of equal surge charge and relative differences among adjacent surge charges. The two different scenarios, equal surge factors versus different surge factors, were meant to evaluate Uber's ability to increase and reallocate supply to surge areas. When the surge multiplier was equal (represented by the black bar) in all six different areas, then the driver did not have a financial incentive to pick one area over another. On the other hand, when one area surges with respect to another, then the driver had a financial incentive to driver to the area with the higher surge multiplier.

[11] State definitions during time interval *t*: *"new"* are drivers that appear for the first time in surge area *s*; *"old"* are drivers that start and end in surge area *s*; *"in"* are drivers that have moved into surge area *s* from an adjacent area; "*out"* are those who have left surge area *s* for an adjacent area; "*dying"* were drivers that had disappeared from surge area *s*.

While Figure 4 is very insightful in depicting future driver behavior, many of the results contradicted the original theory that Uber drivers flock to the areas with higher surge multipliers. This can be seen by looking at the "*out*" state for five of the six areas (M1, M2, M3, SF0, and SF3). The percentage of cars leaving their surging area for another area was greater when their original area had higher surge factors relative to adjacent areas (p. 11). This contradicted Uber's explanation that surge multipliers increase the supply of drivers in a given area. Furthermore, only half of the time was there more cars that moved "*in*" higher surge areas relative to their local areas. On the other hand, they found that higher surge areas only had 3.7% more of "*new*" cars relative to other areas. These results suggested that surge pricing has a limited ability to generate "*new*" supply in surge areas. In other words, surge pricing had a minimal impact on incentivizing offline drivers to go "online" in surge areas. In addition, there was no evidence that surge pricing can significantly reallocate existing supply from other areas to higher surge areas.

3.3 ***"Using Big Data to Estimate Consumer Surplus: The Case of Uber"* By: Peter Cohen, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe (NBER), 2016:**

In *"Using Big Data to Estimate Consumer Surplus: The Case of Uber"*, Cohen et al. collaborated with Uber Technologies Inc. in an attempt to calculate real-life numerical dollar values for consumer surplus from price elasticity derivations[12]. Consumer surplus is defined as the difference between the highest price consumers are willing to pay and the price they ultimately pay. It is calculated in a market as the the area between the price level and the demand curve. In order to calculate consumer surplus, one must know the quantity demanded at every integral price point. It is for this reason that consumer surplus has historically only been discussed in theory or in hypothetical examples. However, with the help of Uber and their proprietary data, Cohen et al. were able to calculate real life estimates of consumer surplus in the ride-hailing market. Similar to the first study in this section by Hall et al. in 2015, Cohen et al. leveraged Uber's digital platform, which enabled them to collect aggregate and granular data across Uber's four largest markets:

[12] Peter Cohen is a Data Scientist at Uber Technologies Inc. with a BA in Economics from the University of Chicago. Robert Hahn is the Director and a professor of Economics at the University of Oxford. Steven Levitt is an Economics professor at the University of Chicago with a PhD in Economics from the Massachusetts Institute of Technology. Robert Metcalfe is Research Scholar at the University of Chicago with a PhD in Economics from the Imperial College London.

Chicago, Los Angeles, New York, and San Francisco. Cohen et al. processed over 50 million total "UberX sessions" spread across the four target markets and all within the first 24 weeks of 2015[13].

In order to ultimately calculate consumer surplus, the authors needed to first estimate price elasticities for supply and demand. They did so by comparing percentage price changes to percentage purchase rate changes. Purchase rate was calculated by dividing the number of requests by the total number of users with the app open over a certain period of time. Again, this derivation of purchase rate was enabled by their use of proprietary Uber data that distinguished between the different types of rider demand. In their results, Cohen et al. claimed that rider demand was "quite inelastic", but don't distinguish between the short-run and long-run. because the percent change increase in price was greater than the resulting percentage decrease in purchasing rate. Once supply and demand curves were derived, they proceeded with a Regression Discontinuity Design (RDD) due to the nature of how surge factors are calculated and implemented, and how geographic areas are defined[14].

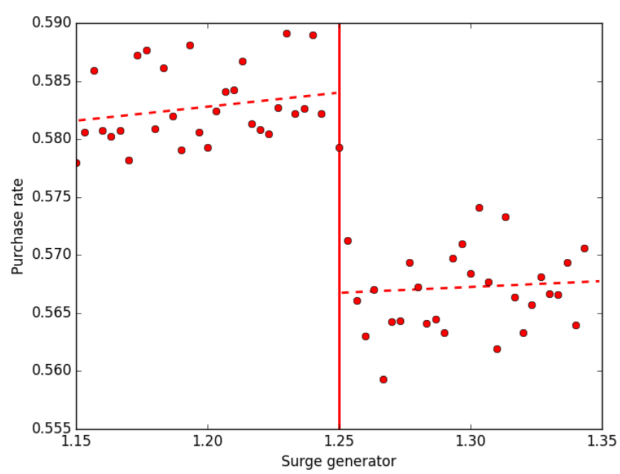

Figure 5: The impact of surge factors on purchase rate given the discontinuity of Uber's surge factors that are calculated to an arbitrary number of decimal points but used as a value that is rounded to one decimal point.

It was estimated that across their four target markets over the first 24 weeks of 2015, there was an estimated $2.88 billion of consumer surplus generated. Furthermore, they extrapolated that $6.76 billion of

[13] Cohen et al. defined an "UberX session" as a user's experience on the rider app whether or not it resulted in a request.
[14] A Regression Discontinuity Design (RDD) is used in order to extract casual effects of an intervention between two similar observations. A certain threshold or cutoff value is identified in order to compare and contrast its affect on observations above and below it.

consumer surplus was generated in the U.S. over the same 24-week period based on the assumption that the percentage of gross U.S. UberX requests that belonged to these cities (approx. 43%) was proportional to total nationwide consumer surplus.

3.4 ***"Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform"*** **By: M. Keith Chen (UCLA) and Michael Sheldon (University of Chicago), 2015:**

In their paper, "*Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform",* Chen and Sheldon analyzed how increased work flexibility and dynamic pricing influenced labor supply in sharing-economy markets.[15] With regard to Uber, they asked how drivers determined when to drive while taking into account self-setting working hours and surge price levels. The motivation for this paper was to revisit findings from previous literature by Camerer et al. (1997) regarding Uber because their drivers are private contractors and not employees. Camerer et al. (1997) claimed that taxi drivers practice a form of income targeting in which they quit driving once they have achieved a certain predetermined level of income, regardless of the current level of fares.

In their analysis, Chen and Sheldon used a data set that consisted of over 25 million UberX trips across five different cities spanning over 9 months from September 2014 to July 2015 (p. 5). In order to maintain some consistency in their analysis, they had to organize their data into working days or shifts. Traditionally, a single working day would coincide with the start and end of a calendar day. However, due to the increased flexibility in working hours and differing fare levels with surge price multipliers, many Uber drivers choose working sessions that include midnight and thus cross over multiple calendar days. Thus, Chen and Sheldon adopted a "flexible session-based approach" that allowed the drivers to set the duration of their working sessions (p. 5). According to this approach, working sessions were defined to be the collection of all trip and application activity that occur without any span of inactivity longer than 4 hours. They chose this approach because their definition of a working session had to balance the increased flexibility in setting one's

[15] Keith Chen is currently a Behavioral Economics Professor at the Anderson School of Management at UCLA. Previously, at the time of this paper, he was the Head of Economic Research at Uber Technologies Inc. He holds a PhD in Economics from Harvard University. Michael Sheldon was an intern at Uber Technologies Inc. at the time of this paper. He holds a BA in Economics from the University of Chicago.

working hours with ensuring that multiple "sessions" were not perceived as one. Four hours was thought to be long enough that drivers were able to complete any errands or tasks that are considered acceptable during flexible working hours (p. 6). Once the data was correctly organized, they were better able to examine how drivers leveraged flexibility in working hours in response to anticipated and unanticipated changes in fare levels through surge multipliers.

The results from by Chen and Sheldon contradicted those from previous literature on income targeting taxi drivers. Chen and Sheldon found that Uber drivers actually choose to extend their working hours during times of surge pricing. These conclusions were drawn for autocorrelations between hourly earnings and hours session length.

Hour	City 1	City 2	City 3	City 4	City 5
0	1.000	1.000	1.000	1.000	1.000
1	0.750	0.611	0.463	0.678	0.745
2	0.538	0.483	0.352	0.480	0.588
3	0.399	0.523	0.300	0.400	0.495
4	0.347	0.473	0.272	0.363	0.459
5	0.336	0.403	0.256	0.308	0.448

All reported statistics are significant at the 0.001 level.

Table 1: Autocorrelation matrix between average hourly income and session length in hours.

In addition, a series of regressions were used to determine the relationship between working session length and fare levels consisted of the Log(HoursOnShift) as the independent variable controlling for weather and day of the week in a given area across all drivers in a certain time interval.

		OLS			2SLS	
Variables:	(1)	(2)	(3)	(4)	(5)	(6)
Log Own Income	0.145***	0.197***	0.168***			
	(0.00144)	(0.00258)	(0.00261)			
Log Average Income				0.292***	0.585***	0.503***
				(0.00237)	(0.00518)	(0.00565)
Constant	1.194***	1.244***	1.341***	1.338***	1.622***	1.671***
	(0.00156)	(0.00251)	(0.00628)	(0.00237)	(0.00504)	(0.00783)
Weather Controls			X			X
Fixed Effects:						
Partner		X	X		X	X
Month and Day of Week			X			X
Observations	2,377,210	2,377,210	2,368,340	2,377,210	2,377,210	2,368,340
Number of Partners	63,830	63,830	63,830	63,830	63,830	63,830
R^2	0.007	0.013	0.038			

All regressions are OLS and 2SLS regressions with Log(Session Length) as the dependant variable.
We report robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$.

Table 2: Log(HoursOnShift) regression results for both OLS and 2LS regression methods

The resulting regression coefficients suggested that session length had an elasticity of .503 significant at the .01 level (p. 8). This implied that session lengths were very responsive to increases in average driver income. Thus, this suggested that their findings coincided more with income maximization rather than income targeting behavior.

4. METHODOLOGY:

This paper's assessment of surge pricing's effectiveness in equilibrating supply and demand during times of market shock requires a detailed data set with insight into Uber rides including time of request, origin, destination, and fare estimate for the different types of services in the location. This will highlight the different behaviors of the Uber services amidst surge pricing. Furthermore, the data needs to span a certain time interval in order to capture fully any shocks and resulting responses to these market changes.

4.1 Uber API:

While Uber did not provide publically available data sets that include the information stated above, there is a method to obtain such data by leveraging the functionality of Uber's API. This use of Uber's API is similar to how Chen et al. (2015) at Northeastern University collected their data. Due to Uber's API structure, two different API calls were required to gather all the information regarding a single ride request estimate: "GET/estimates/time" and "GET/estimates/price". Each ride request had to be given origin and destination longitude and latitude. The responses from the two API calls consisted of:

- fare estimates
- expected trip distance
- expected trip duration
- ETA of driver to passenger pick-up location[16]

This data was received in a JSON format that needed to be unpackaged to extract the values.[17] Uber sets a limit of 2,000 requests per hour per token. Thus, in order to circumvent this request limit, multiple

[16] It is important to note that Uber calculates Driver ETA in seconds but it is communicated to the rider as a value rounded to the closest whole minute.
[17] JSON (JavaScript Object Notation) is a digital format that both facilitates human readability and machine parsing.

Uber API server tokens were obtained in order to act as different fictitious Uber “accounts”. This ensured that the maximum number of requests per token was not reached.

4.2 Python Application:

By writing a program in Python that is able to automate simulated ride requests, it is possible to save this data in an Excel file. The automation is done by a task scheduler on the client’s server that pings the Uber servers with imputed origin and destination information in order to receive a fare estimate in return. In order to capture the full effect of changes in supply and demand, the interval of requests was every 30 seconds. In addition, in order to ensure all market behaviors were captured, requests estimates were focused on one single origin-destination (OD) pair. For this analysis, the OD pair between Boston College and TD Garden in Boston was chosen because of TD Garden’s susceptibility to different market conditions as a result of athletic and other entertainment events.

4.3 Data Description:

In aggregate, over 120,000 ride requests over 2 months for the Boston College – TD Garden OD pair were collected for this analysis. These requests spanned all of Uber’s service offerings including UberPOOL, UberX, UberXL, UberBLACK, and UberSUV[18]. The data sets were formed in order to capture different market conditions including shocks to levels of supply and demand (i.e. athletic events and concerts) as well as their respective control conditions (same time and day of the week, but no event at TD Garden). More specifically, below is an outline of the different data sets collected (all data sets were from 2pm – 2am):

- Boston Celtics Games: 2/27, 3/1, 3/22
- Boston Bruins Games: 2/28, 3/2, 3/23
- Ariana Grande Concert: 3/1
- Control Conditions: 2/21, 2/24, 2/25

[18] A screenshot of the data can be seen in Figure 2 in the Appendix.

5. ANALYSIS:

In this section we analyze the multiple ride-request datasets collected by the Python program in order to highlight the remaining market inefficiencies despite surge pricing. To do so, an initial analysis of the data's general characteristics, as well as validation of the data's accuracy, provides greater understanding of surge pricing and how the different Uber services compare to each other.

5.2 Data Validation:

The datasets consist of ride request estimates including fare (dollars), distance (miles), duration (minutes), and estimated time of arrival of driver in minutes (ETA) at an individual profile level. From these parameters, the surge factor associated with each fare is derived by the fare function and city-specific values provided on Uber's website:

$$\boldsymbol{Fare = BookingFee + Surge*(BaseFare + MileageRate*X_{MILES} + TimeRate*X_{MINUTES})}$$

$$\boldsymbol{Fare_{BOSTON} = 1.35 + Surge*(2.00 + 1.24*X_{MILES} + 0.20*X_{MINUTES})}$$

Using this fare equation for UberX services, the fare-specific surge factor for an individual request was calculated. It is important to remember that Uber rounds their surge factors to one decimal point when charging the rider the final fare. In order to confirm the validity of the data, an Ordinary Least Squared (OLS) regression on *Fares* with interaction variables between *Surge* and *MileageRate* as well as *Surge* and *TimeRate* was completed to emulate Uber's fare function. The table below displays the abbreviated results of this regression:

R-Squared	0.992					
	Coefficients	*Uber Values*	*t-Statistic*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1.662	1.35	28.896	4.214E-151	1.550	1.776
Duration*Surge	0.196	.20	87.218	0	0.192	0.201
Distance*Surge	1.225	1.24	219.891	0	1.214	1.236
Surge	1.954	2.00	27.845	3.781E-142	1.817	2.092

Table 3: Results of an OLS regression of the collected data in order to confirm the data's accuracy according to Uber's fare breakdown. These coefficients statistically significantly resemble those values provided by Uber on their own website.

The regression results confirm the validity of that data and the accuracy of Uber's initial fare estimates. As seen in the R-Squared value, just over 99% of the variance in estimated fares can be explained by the variance in the variables: *Surge, Duration*Surge,* and *Distance*Surge.* In addition, the coefficients of the variables very closely resemble the actual Boston rates and fees charged by Uber.

5.1 Discussion of Data:

Having confirmed that these fare estimates correctly reflect Uber's fare components, an analysis between Uber's fare function and Boston metered taxis explains why one of the key drivers of Uber's massive growth in urban markets has been its frequently lower fares compared to traditional urban taxi fleets. Boston taxi rates and fees are provided online to the public by the Boston Police Department.[19]

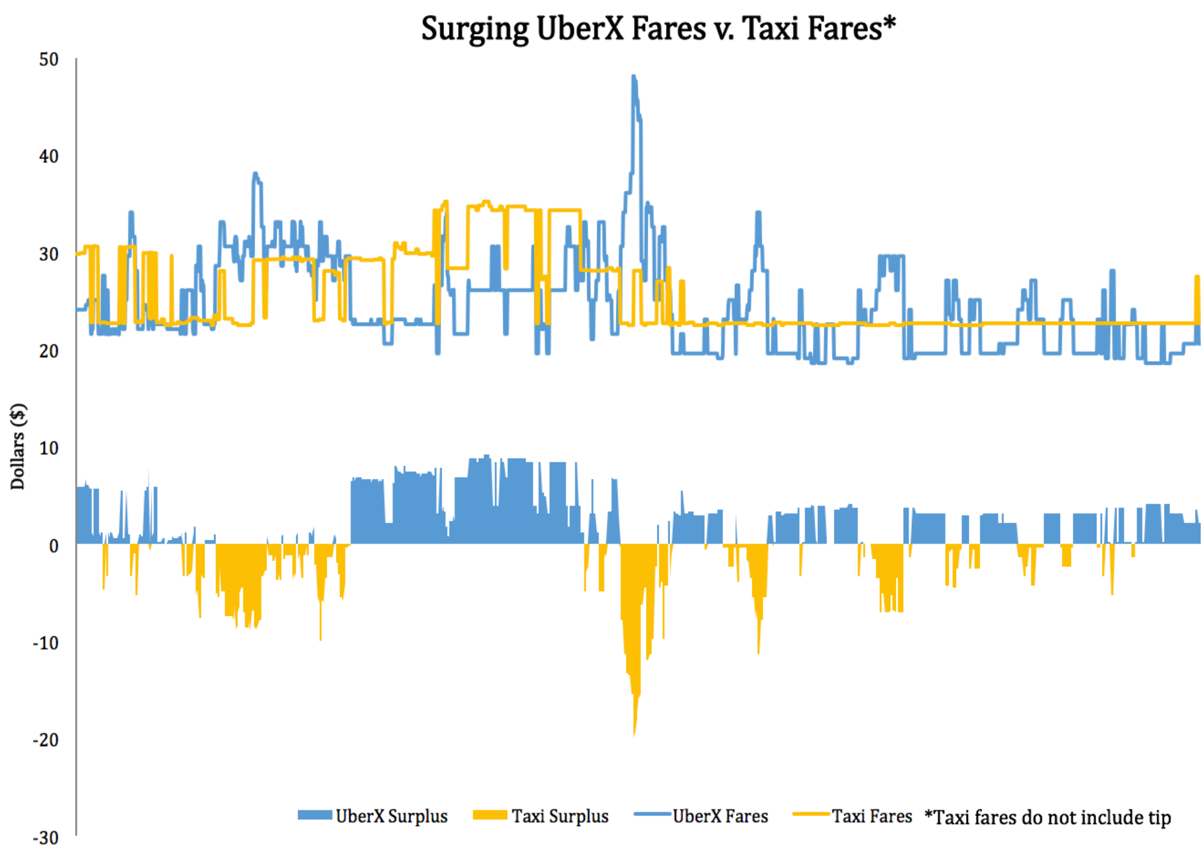

Figure 6a: Fare values according to UberX rates and fees as well as Boston taxi rates and fees. Solid shaded area represents difference between expected UberX fares and Boston taxi fares from TD Garden to Boston College on March 23rd 2017.

[19] Official Website of the Boston Police Department; www.bpdnews.com/taxi-rates

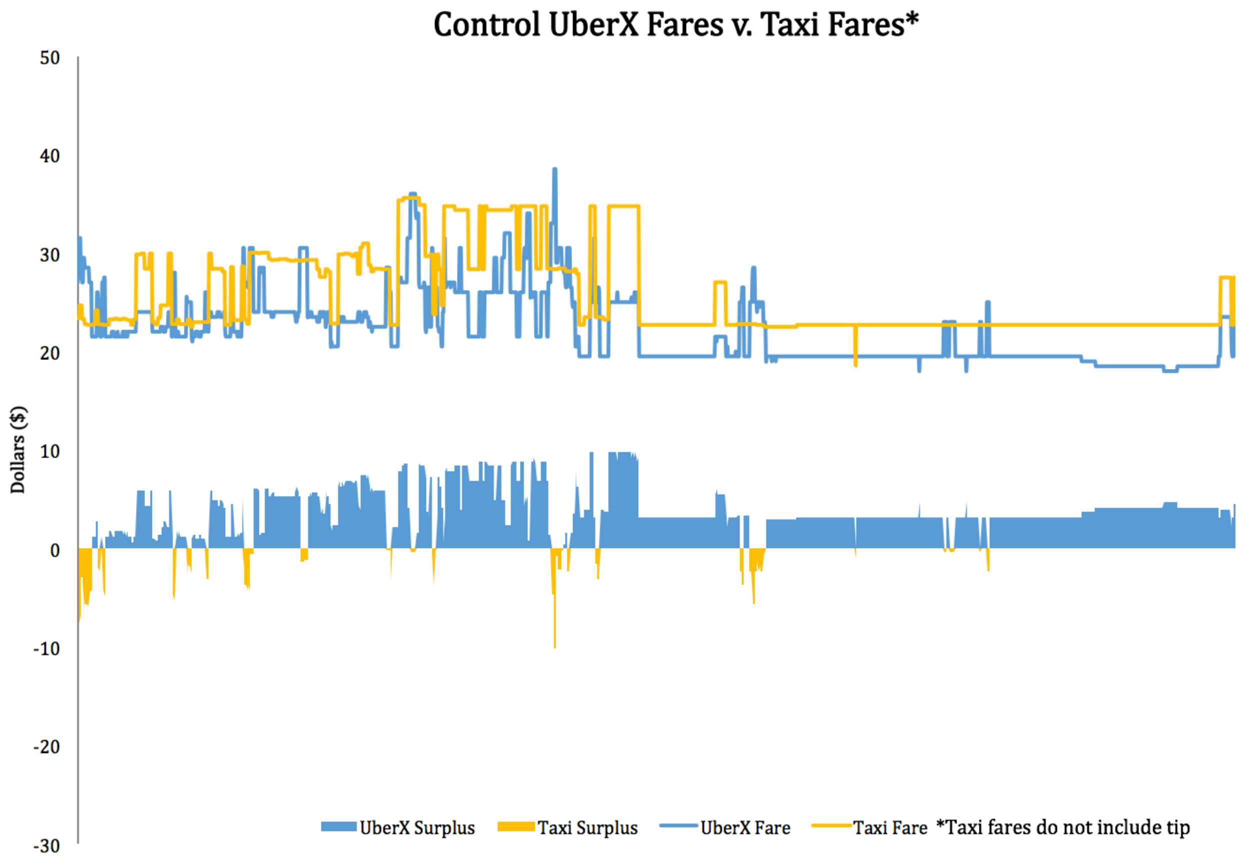

Figure 6b: Fare values according to UberX rates and fees as well as Boston taxi rates and fees. Solid shaded area represents difference between expected UberX fares and Boston taxi fares from TD Garden to Boston College on March 27th 2017.

Using the "Distance" and "Duration" parameters from the Uber API response, a corresponding expected Boston taxi fare can be calculated. Taxi rates are $2.60 for the first 1/7 of a mile. Then, $0.40 for each 1/7 of a mile thereafter. Figures 6a and 6b represent the expected fares for UberX and a Boston metered taxi as well as the difference in fares between UberX and taxis represented by the shaded regions. Figure 6a is during a time of surge pricing in the area due to a Bruins game while Figure 6b is during control market conditions with no event at TD Garden. By graphing the difference in fares, Uber's ability to charge lower prices than Boston taxis is illustrated.[20] According to these graphs, one is able to conclude that Uber is able to charge a lower fare for a larger proportion of rides in both of these time frames than Boston taxis despite their

[20] It is important to note that the calculated taxi fares do not include tip. Secondly, there is no ability to tip on the Uber platform making all Uber fares final.

surge pricing. Furthermore, the times that Boston taxis are able to offer lower fares are often while Uber is surging, implying that demand exceeds supply. Due to both regulated supply and fixed pricing model, Boston taxis are less expensive during surge periods, but they are unlikely to be available in adequate quantity to meet rider demand during these periods. Therefore, many riders would be unable to find an available Boston taxi to take advantage of these lower fares.

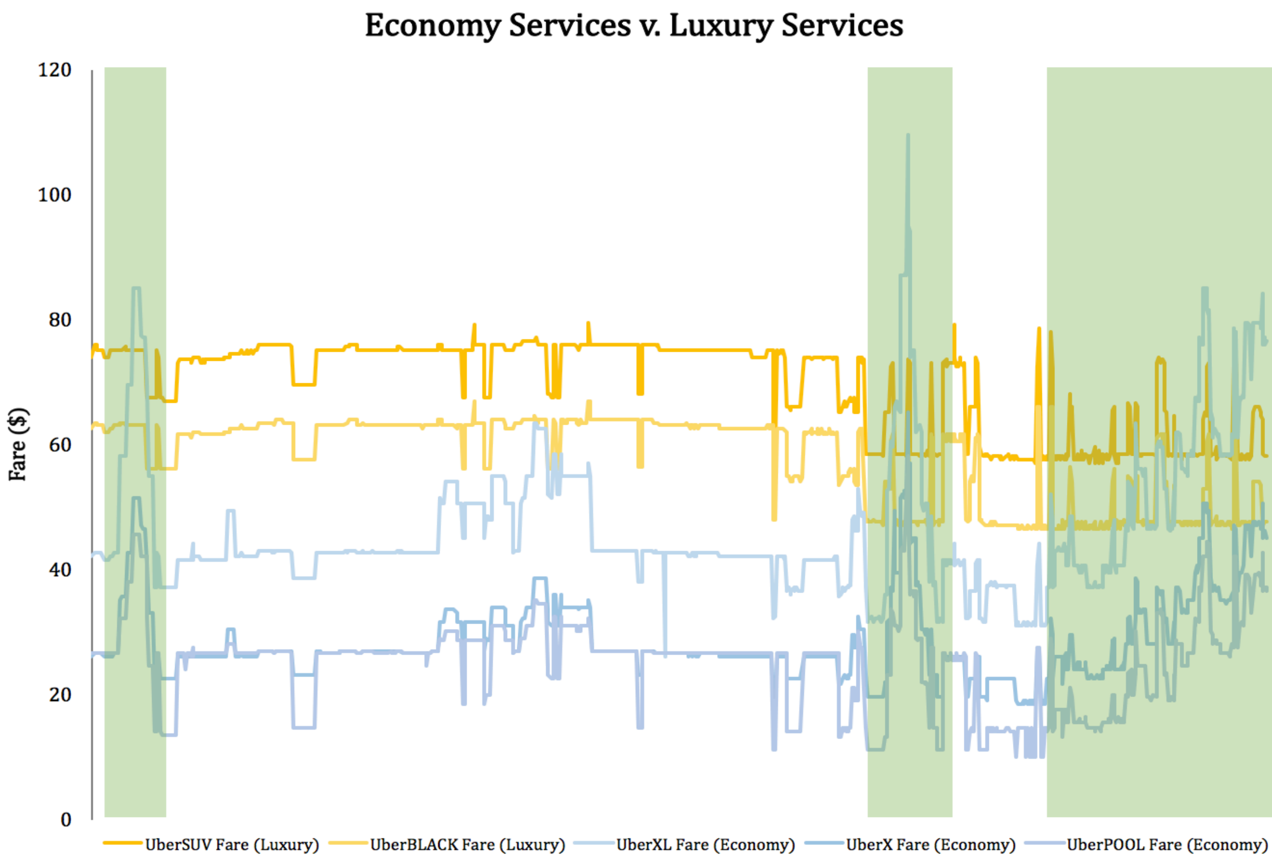

Figure 7: Fare values comparing the different classes of Uber services on February 25, 2017.

Uber implements a dynamic pricing model on both their economy and luxury transportation service classes. However, the timing, magnitude, and duration of these changes in prices are different between the two classes. Figure 7 depicts the movement of predicted fares from 2:00PM to 2:00AM on Saturday March 4th for ride requests from TD Garden to Boston College. The results in Figure 7 represent the similarities in fare movement for the services in each type of service class. The services in the economy class, UberPOOL, UberX, and UberXL, all follow a very similar trend in movement of fares while the services in the luxury class, UberBLACK and UberSUV, both follow their own different changes in fare. In Figure 7, the green-shaded areas represent timeframes in which the movement of fares differed substantially between the economy and luxury class of services based on observation. There is a striking dissimilarity between the economy services that were highly impacted by surge pricing and the luxury services that experienced significantly less surge pricing. This difference can be attributable to the different shifts in market conditions for each of the classes.

	UberPOOL		**UberX**		**UberXL**		**UberSUV**		**UberBLACK**	
	Fare	ETA	Fare	ETA	Fare	ETA	Fare	ETA	Fare	ETA
Mean	$24.92	3.14	$28.68	3.00	$46.74	4.10	$69.50	4.11	$57.79	3.57
Standard Dev.	$7.18	1.21	$6.71	1.16	$11.43	1.49	$7.35	1.15	$6.83	1.04
Percent Dev.	**29%**		**23%**		**24%**		11%		12%	
Median	26.5	3	26.5	3	42.5	4	74	4	62	4
Mode	$26.50	2.00	$26.00	2.00	$42.50	4.00	$75.00	4.00	$63.00	4.00
Minimum	10	1	18.5	1	26	1	57	2	46.5	2
Maximum	58	9	65	9	109.5	10	79.5	8	67	8

Table 4: Summary statistics for the data in Figure 7.

The summary statistics also provide insight in the difference between the two classes of service. As seen in the higher percent deviation for the economy class services than luxury services, economy services experience greater shifts in market conditions which suggests that they are better proxies for changes in rider demand and driver supply.

It is reasonable to expect that a greater number of riders would request the lower-fare, higher-availability services such as UberX, UberXL, and UberPOOL. This logic explains the difference in fare movements between the two classes in the right-most shaded area. As more riders begin to head home after spending a night in Boston, more riders will request the economy services than luxury services. In order to substantiate these claims, correlation matrices between the services can quantify the similarities within each of the classes as well as the difference between the two classes. Tables 5a and 5b display fare and driver ETA correlations respectively.

Fare Correlation Matrix:	UberX	UberXL	UberPOOL	UberBLACK	UberSUV
UberX	1				
UberXL	0.99	1			
UberPOOL	0.81	0.76	1		
UberBLACK	0.22	0.15	0.61	1	
UberSUV	0.21	0.15	0.60	0.99	1

Table 5a: Correlations of fare between Uber's service offerings for 1,500 observations for each service. Correlations shaded in green represent the economy class and yellow is the luxury class.

ETA Correlation Matrix:	UberX	UberXL	UberPOOL	UberBLACK	UberSUV
UberX	1				
UberXL	0.54	1			
UberPOOL	0.88	0.56	1		
UberBLACK	0.17	0.23	0.19	1	
UberSUV	0.21	0.32	0.244	0.83	1

Table 5b: Correlations of driver ETA between Uber's service offerings for 1,500 observations for each service. Correlations shaded in green represent the economy class and yellow is the luxury class.

In Table 5a, there is a clear correlative relationship among the economy class services and as well as between the luxury class services. This implies that each pricing model for the two classes has been built in order to impact each of the services in the classes equally. Furthermore, in Table 5b, the strong correlative relationship between the services in each class is upheld. For example, when driver ETA for UberX increases, UberPOOL follows closely a similar increase in ETA. These results coincide with the assumption that similar types of services (i.e. small-sedan and low-fare) would respond similarly to shifts in market conditions. Thus, for the purposes of this paper, the analysis focuses only on the economy class and specifically on the UberX service, since it the most widely used by consumers and thus better reflects shifts in market conditions[21].

5.3 Ariana Grande Concert:

The first specific dataset that this paper focuses on consists of ride-request estimates that capture the market before, during, and after an Ariana Grande concert at TD Garden in Boston, MA on March 3rd, 2017.

[21] Chen et al. (2015)

This is a critical dataset because it allows for a direct comparison to Uber's in-house case study on the effects of surge pricing by Jonathan Hall et al (2015). In order to correctly interpret the market activity, a timeline for this event was confirmed by Maura Johnston, a Boston Globe journalist, who attended the concert. This is important because it enables an analysis of critical time frames such as at the beginning of the concert as supply flooded the area due to passenger drop-offs and again once the concert ended and there was a spike in demand.

In order to confirm that the only difference between the control data set and the actual concert data set was the concert itself, sample variances needed to be compared. Therefore, two statistical F-tests were conducted on different portions of the data. The first was on data up until the concert. The second F-test was during and after the concert. As seen in the results in Table 1 in the Appendix, for data before the concert, the null hypothesis that the two sample variances are equal *cannot* be rejected. On the other hand, the second F-test yielded very different results that concluded the null hypothesis *can* be rejected on the portions of data during and after the concert.

In order to display this empirical data, a 6-period moving average trend line was plotted for both *Fare* and *ETA* for 1,500 observations. A 6-period moving average was chosen because the Python program pinged the Uber servers every 30 seconds and surge factors are expected to be reevaluated every 3-5 minutes. The results in Figure 8 focus on the end of the concert when there was an expected spike in demand.

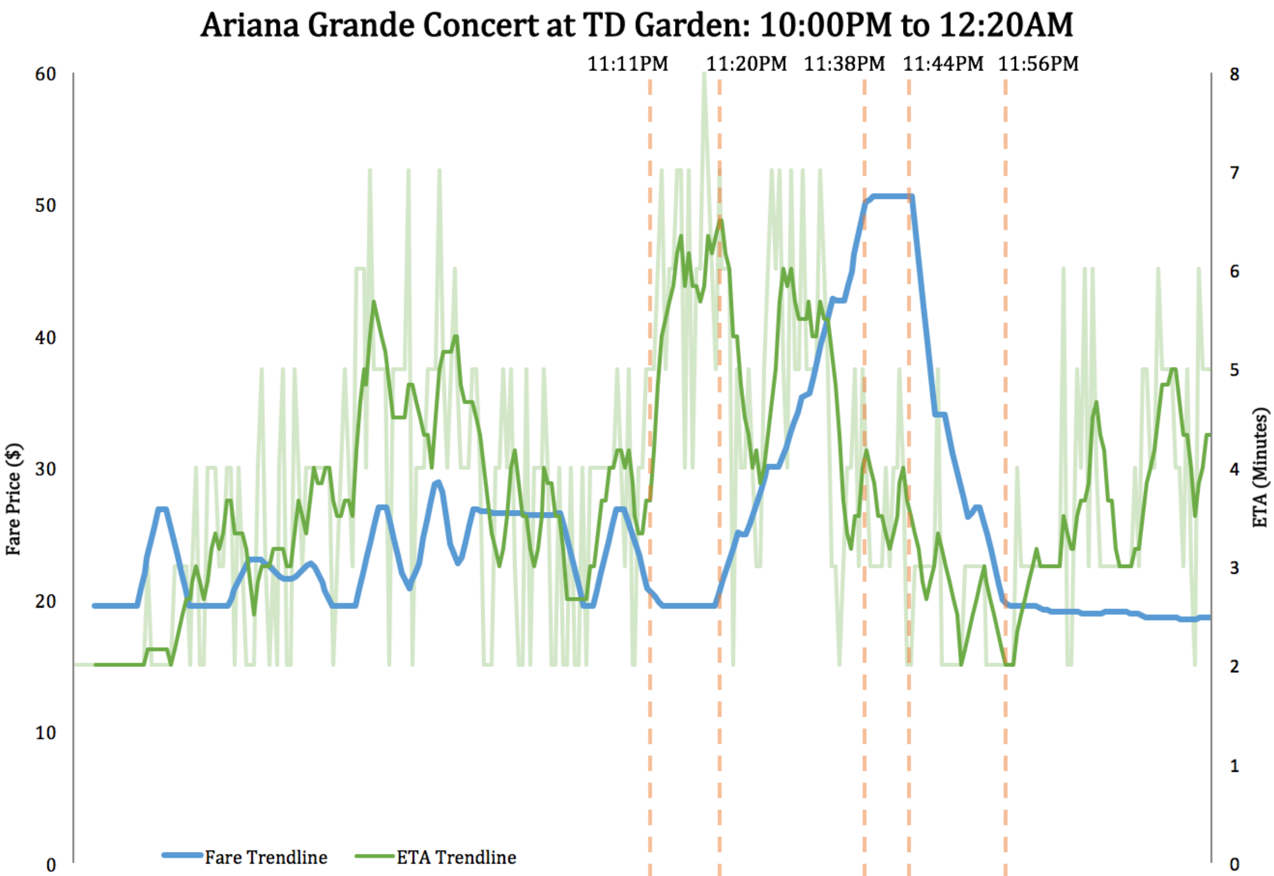

Figure 8: Concert data consisting of Fare plotted along the primary y-axis on the left in blue as a 6-period moving average trend line. ETA, in green, is plotted along the secondary y-axis on the right-hand side. The **BOLD** trend line is a 6-period moving average and the faint green is the actual volatility in ETA.

Figure 8 confirms the timeline provided by the Boston Globe as we see an increase in ETA at 11:11PM and the concert was over "around 11pm". An increase in ETA represents a depletion of the existing supply already in the area. This trend continues until it results in an increase in fare. On the graph, ETA peaks at the same time as fare begins to increase at 11:20PM. From then until 11:38PM, the increasing fare is a result of a surge factor greater than 1. The trends in *ETA* and *Fare* in Figure 8 are also very similar to the trends found during the Ariana Grande concert on March 21st, 2015 at Madison Square Garden in the Uber case study by Hall et al. as seen in Figure 2a. This confirms the two concerts resulted in similar market shifts. Between 11:20PM and 11:38PM, as fare is increasing there is a decrease in ETA which implies that the higher fares are subsequently attracting driver supply to the area as well as limiting demand to only those consumers with a high enough willingness to pay. This occurs until 11:44PM, which marks the point that supply levels are sufficient to serve the remaining demand in the area and fare begins to converge back to its normal level. Finally, at 11:56PM, ETA increases again as drivers are no longer attracted to the area. In order to highlight the magnitude of these changes in ETA and fares, Figure 8 can be compared to Figure 9. Figure 9 displays the same data but collected a week before on February 22nd when there were no events at TD Garden.

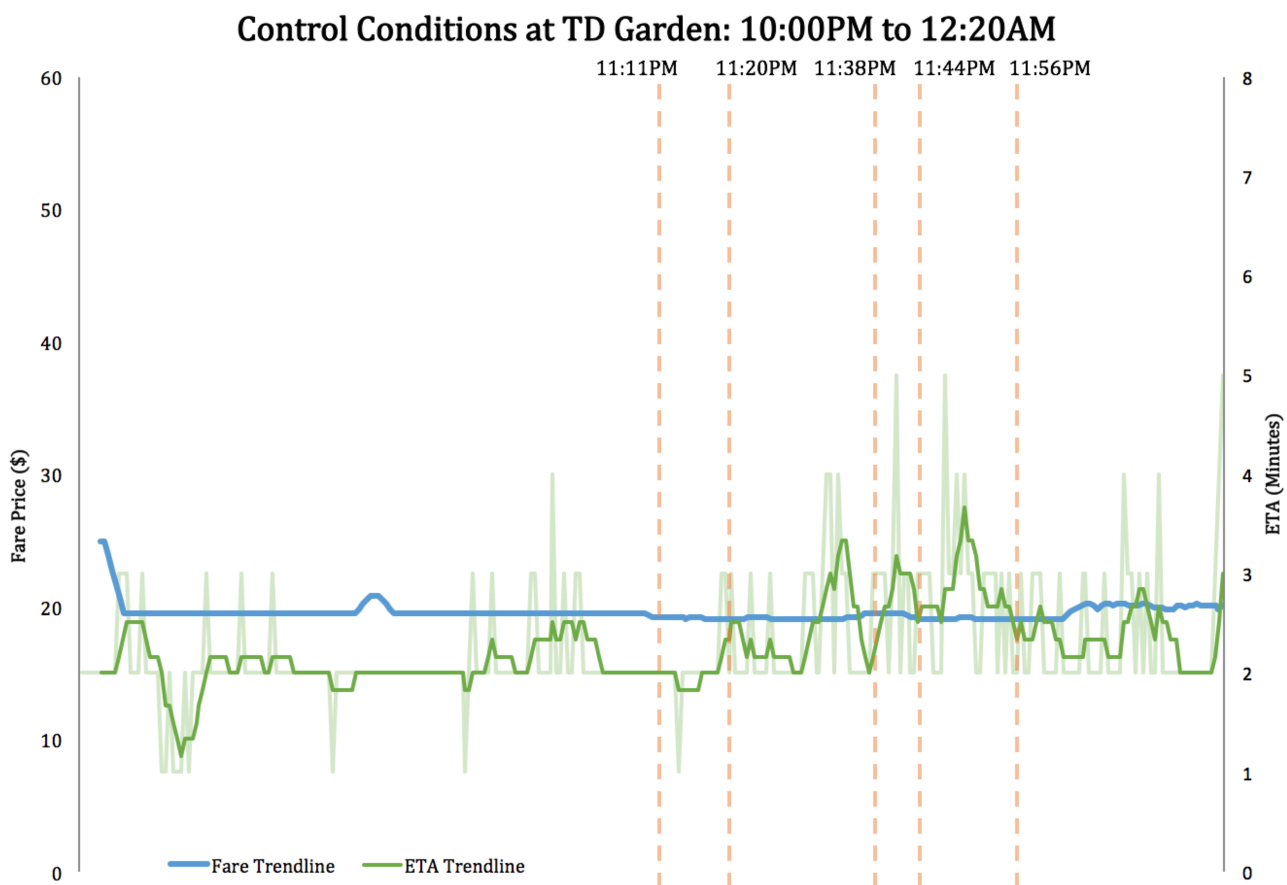

Figure 9: Control data consisting of Fare plotted along the primary y-axis on the left in blue as a 6-period moving average trend line. ETA, in green, is plotted along the secondary y-axis on the right-hand side. The **BOLD** trend line is a 6-period moving average and the faint green is the actual volatility in ETA.

While the effectiveness of surge pricing is evident in the graph as a result of falling ETA levels, market inefficiencies can be identified. The changing levels of ETA in Figure 8 represent a lag between increasing levels of demand and the availability of sufficient supply in the area. Levels of supply are inherently fixed at any single moment in time because drivers must invest the time and effort to drive to TD Garden. Ideally, Uber would be able to correctly forecast levels of demand in order to incentivize drivers to serve certain areas and be able to offer a consistent ETA. However, we see that this obviously not the case, with ETA levels ranging from 1 to 8 minutes. Based on the movements observed in this time series graph, we are able to construct an economic model that represents the differences in supply and demand elasticity between the long-run and short-run.

5.4 Market Elasticity Model:

An economic model that represents the short-run inelasticity and long-run elasticity of the market for Uber drivers can be derived from the time series data collected around the Ariana Grande concert in Figure 8. The derivation of the model highlights how riders make decisions and act in the short-run, making quantity demanded more elastic in response to shifting market conditions. On the other hand, drivers are able to make decisions in the short-run but are only able to act in the long-run because of the time it takes to drive to the surge area. This inherently makes supply perfectly inelastic (fixed) in the short-run. Next are explanation of points and shifts of curves on the graph.

- A: Equilibrium price before the demand shock. Existing supply levels are sufficient to serve current demand (11:11PM – 11:20PM in Figure 8)
- From A to B: Ride demand increases, shifting the demand curve outward from D_0 to D_1 (11:20PM – 11:38PM in Figure 8). Given the perfectly inelastic supply in the short run, when demand increases, fares increase as a result of surge pricing trying to equilibrate supply and demand.
- From B to C: Higher fares for drivers attract greater supply, shifting the supply curve outwards from S_0 to S_1. Supply increases until the price is driven back to the original equilibrium level at P_{Eq} and supply at S_1 (11:44PM – 11:56PM in Figure 8)
- From C to A: As demand returns to its pre-shock levels, supply also retracts until the market returns to the original equilibrium level at P_{Eq} at S_0

  (11:56PM – 12:20AM in Figure 8)

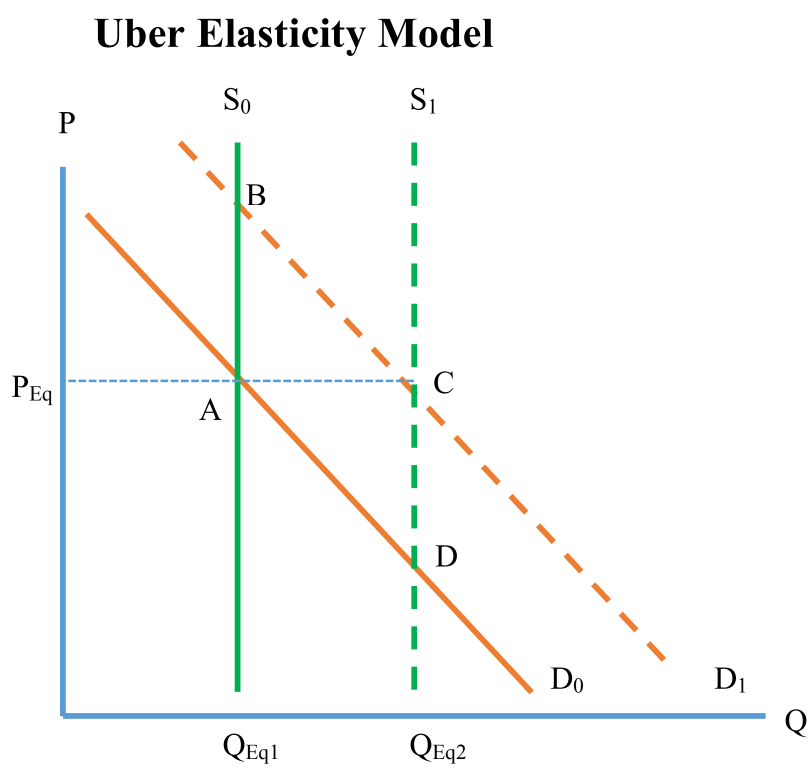

Figure 10: An elasticity model derived from the empirical data from the March 3rd, 2017 Ariana Grande concert at TD Garden, Boston, MA.

Notably, the Uber pricing model does not obey fully the fundamental laws of supply and demand and thus is not conducive to creating a perfectly competitive market. For example, Uber sets a "base fare" that acts as a price floor. This minimum fare is set by Uber as the equilibrium market price during normal market conditions rather than being established dynamically by market factors such as levels of supply and demand. In Figure 10, P_{Eq} represents Uber's base fare for the OD pair between TD Garden and Boston College. However, while Uber will allow its prices to increase in order to equilibrate supply and demand (i.e. surge price level at point B in Figure 10), fares will never drop below P_{Eq} even if market conditions suggest an "equilibrium market" price below Uber's minimum fare (i.e. price level at point D in Figure 10). When supply exceeds demand, Uber would rather wait to clear the market of the surplus of drivers than lower the price. This surplus of supply could result from either an over response by drivers to the surge areas or any late responses by drivers. In either case, an oversupply of drivers results in frustrated drivers who were expecting to earn increased fare and are now discouraged from pursuing surge areas in the future. In surge pricing scenarios, driver testimonials indicate that the key uncertainties for drivers are how long it will take to reach the surge area and how long the surge is expected to last in that area. Many seasoned Uber drivers stated in testimonials that they often avoid altering their driving schedules during surge pricing or even avoid chasing surge pricing from one region into another because of the uncertainty regarding the opportunity cost of traveling to the surge region.[22] The insights from these driver testimonials also coincide with the conclusions from the paper by Chen et al. from Northeastern University that portray driver state-machine transition probabilities that contradict Uber's intentions of surge pricing.[23] These uncertainties undermine Uber's ability to use surge pricing to quickly alleviate driver shortages.

6. <u>CONCLUSION:</u>

Uber's platform has disrupted the historically inefficient and highly regulated ride-hailing industry with its digital platform that facilitates the matching of drivers and riders, seeks to provide consistent driver

[22] Richardson, Anthony. Personal Interview, (February 21, 2017).
[23] Refer to Figure 4 in this paper for the state-machine transition probability diagram

availability, and simplifies fare payment between the driver and rider. Uber does so by pricing their services at a level that is appropriate for current market conditions. However, this paper identifies the limitations of Uber's ability to eliminate market inefficiencies despite their innovative dynamic pricing model, especially in the short-run. The data sets presented in this paper consisted of over 120,000 rides over two months, which enabled to capture the full spectrum of market behaviors. Through the analysis of supply and demand elasticity between the long-run and the short-run, there were still periods in which levels of supply and demand were not equilibrated correctly due to discrepancies between driver elasticity in the short-run and the long-run. In addition, Uber does not allow the market to set its own market price. Uber's fare components identify an equilibrium market price, which is also the minimum fare. While fares are able to increase above the minimum fare, they are unable to fall below the minimum fare even if market factors such as supply and demand suggest a lower market price.

If Uber seeks to bring even greater efficiency to the ride-hailing market, particularly in the early stages of an increase in demand, the company might consider changing some of the core elements of its current platform. Such changes might include the driver compensation structure or gaining total control over its driver supply. By identifying different metrics by which to compensate drivers, Uber may be able to better influence driver behavior. For example, Uber could introduce compensation for the time it takes drivers to travel to surge areas from other areas or a different rate for the time they remain idle in surge areas just before an anticipated spike in demand. If Uber wishes to gain total control over its supply, it might have to hire the drivers as Uber employees. Hiring employee drivers, however, represents a major change in Uber's operations and transforms Uber from a technology company to a transportation company. More futuristically, Uber is already testing driverless cars, which would allow the company to allocate driver supply as it wishes while still remaining a technology company with a digital platform that matches cars to riders.[24] The actions and results of Uber, as a pioneer in the sharing economy, will be watched closely by both related and unrelated sharing platforms.

[24] Chafkin, Max (Bloomberg Businessweek, 2016).

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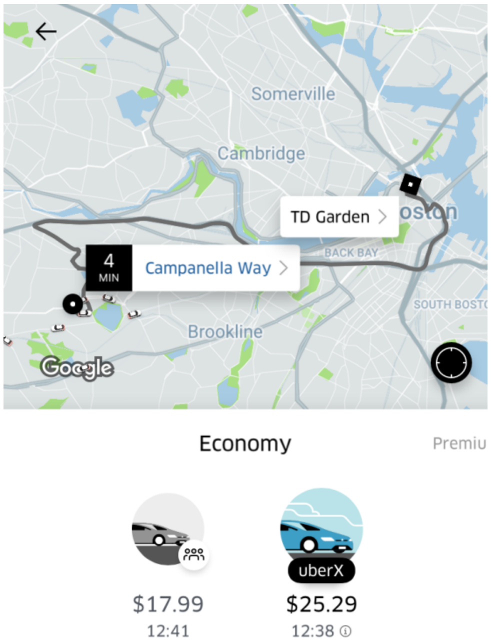
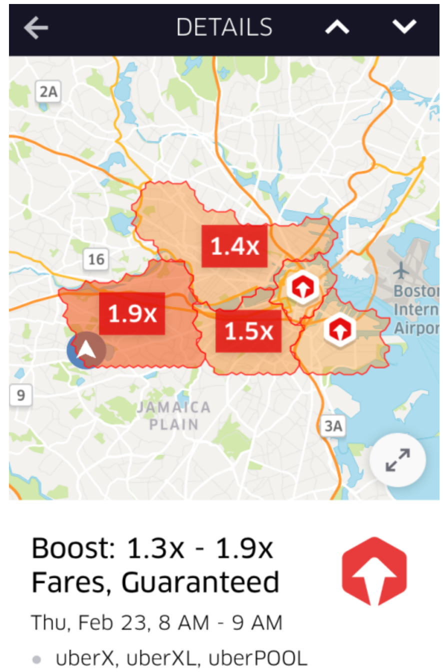
8. APPENDIX:

Figure 1: Uber Application Differences





Uber Rider Application

Uber Driver-Partner Application

Table 1: F-Test Results Comparison:

Pre Concert Fares:	***Control Fare***	***Ariana Grande Fare***
Mean	24.707	24.447
Variance	18.506	16.900
Observations	690	690
df	689	689
F	1.095	
P(F<=f) one-tail	0.117	**Cannot Reject H_0**
F Critical one-tail	1.134	
Concert Fares:	***Ariana Grande Fare***	***Control Fare***
Mean	25.208	19.575
Variance	71.553	0.897
Observations	301	301
df	300	300
F	79.778	
P(F<=f) one-tail	5.973E-199	**Able to Reject H_0**
F Critical one-tail	1.210	

Table 1: F-test results for Pre-concert fares (in blue) and concert fares (in orange). F-tests calculate sample variance ratios in order to determine whether the two samples are statistically different or not. From these results, the null hypothesis *cannot* be rejected for pre-concert fares but *can* be for concert fares.

Figure 2: Data set screenshot:

Time_Stamp	UberX					UberBLACK					UberXL					UberPOOL					UberSUV				
	Fare	Duration	Distance	Surge	ETA	Fare	Duration	Distance	Surge	ETA	Fare	Duration	Distance	Surge	ETA	Fare	Duration	Distance	Surge	ETA	Fare	Duration	Distance	Surge	ETA
2017-03-27T15:00:03	27	23	7.54	1.6	300	52	23	7.54	1	240	45	23	7.54	1	300	22	23	7.54	1	300	63.5	23	7.54	1	240
2017-03-27T15:00:32	27	23	7.54	1.6	300	52	23	7.54	1	120	45	23	7.54	1	360	22	23	7.54	1	300	63.5	23	7.54	1	120
2017-03-27T15:01:01	31	23	7.54	1.9	240	52	23	7.54	1	240	51.5	23	7.54	1	300	27	23	7.54	1	240	63.5	23	7.54	1	240
2017-03-27T15:01:30	31	23	7.54	1.9	240	52	23	7.54	1	180	51.5	23	7.54	1	360	27	23	7.54	1	240	63.5	23	7.54	1	180
2017-03-27T15:01:59	31.5	23	8.01	1.8	300	53.5	23	8.01	1	120	53	23	8.01	1	360	28	23	8.01	1	300	65	23	8.01	1	120
2017-03-27T15:02:27	31.5	23	8.01	1.8	180	53.5	23	8.01	1	120	53	23	8.01	1	240	28	23	8.01	1	180	65	23	8.01	1	120
2017-03-27T15:02:56	27.5	23	8.01	1.6	300	53.5	23	8.01	1	120	46	23	8.01	1	360	23	23	8.01	1	300	65	23	8.01	1	120
2017-03-27T15:03:24	27.5	23	8.01	1.6	240	53.5	23	8.01	1	120	46	23	8.01	1	240	23	23	8.01	1	240	65	23	8.01	1	120
2017-03-27T15:03:52	27	24	7.51	1.6	240	52	24	7.51	1	120	45	24	7.51	1	360	22	24	7.51	1	240	63.5	24	7.51	1	180
2017-03-27T15:04:21	27	24	7.51	1.6	180	52	24	7.51	1	120	45	24	7.51	1	480	22	24	7.51	1	180	63.5	24	7.51	1	240
2017-03-27T15:04:50	29.5	24	7.51	1.7	240	52	24	7.51	1	120	48.5	24	7.51	1	360	24.5	24	7.51	1	240	63.5	24	7.51	1	240
2017-03-27T15:05:19	29.5	24	7.51	1.7	300	52	24	7.51	1	120	48.5	24	7.51	1	360	24.5	24	7.51	1	300	63.5	24	7.51	1	240
2017-03-27T15:05:47	28.5	23	7.33	1.7	300	51.5	23	7.33	1	120	48	23	7.33	1	360	24.5	23	7.33	1	300	62.5	23	7.33	1	240
2017-03-27T15:06:16	28.5	23	7.33	1.7	300	51.5	23	7.33	1	120	48	23	7.33	1	360	24.5	23	7.33	1	300	62.5	23	7.33	1	240
2017-03-27T15:06:44	28.5	23	7.33	1.7	240	51.5	23	7.33	1	120	48	23	7.33	1	300	24.5	23	7.33	1	240	62.5	23	7.33	1	240
2017-03-27T15:07:13	28.5	23	7.33	1.7	240	51.5	23	7.33	1	120	48	23	7.33	1	300	24.5	23	7.33	1	240	62.5	23	7.33	1	240
2017-03-27T15:07:42	28.5	24	7.3	1.7	120	51.5	24	7.3	1	120	48	24	7.3	1	420	24.5	24	7.3	1	120	63	24	7.3	1	240
2017-03-27T15:08:10	28.5	24	7.3	1.7	120	51.5	24	7.3	1	180	48	24	7.3	1	480	24.5	24	7.3	1	120	63	24	7.3	1	180
2017-03-27T15:08:38	28.5	24	7.3	1.7	120	51.5	24	7.3	1	180	48	24	7.3	1	360	24.5	24	7.3	1	120	63	24	7.3	1	180
2017-03-27T15:09:07	27	24	7.3	1.6	120	51.5	24	7.3	1	180	45	24	7.3	1	480	22	24	7.3	1	120	63	24	7.3	1	180
2017-03-27T15:09:36	27	24	7.3	1.6	120	51.5	24	7.3	1	240	45	24	7.3	1	300	22	24	7.3	1	120	63	24	7.3	1	300
2017-03-27T15:10:04	27	23	7.3	1.6	240	51.5	23	7.3	1	300	45	23	7.3	1	300	22	23	7.3	1	240	63	23	7.3	1	300
2017-03-27T15:10:33	27	23	7.3	1.6	240	51.5	23	7.3	1	300	45	23	7.3	1	300	22	23	7.3	1	240	63	23	7.3	1	300
2017-03-27T15:11:01	21.5	23	7.3	1.3	240	52	23	7.3	1	300	35	23	7.3	1	300	14.5	23	7.3	1	240	63	23	7.3	1	300
2017-03-27T15:11:31	21.5	23	7.3	1.3	240	51.5	23	7.3	1	300	35	23	7.3	1	300	14.5	23	7.3	1	240	63	23	7.3	1	300
2017-03-27T15:12:00	21.5	23	7.32	1.3	240	52	23	7.32	1	300	35	23	7.32	1	300	14.5	23	7.32	1	240	63	23	7.32	1	300
2017-03-27T15:12:28	21.5	23	7.32	1.3	180	52	23	7.32	1	240	35	23	7.32	1	300	14.5	23	7.32	1	240	63	23	7.32	1	300
2017-03-27T15:12:56	21.5	23	7.32	1.3	240	52	23	7.32	1	240	35	23	7.32	1	300	14.5	23	7.32	1	240	63	23	7.32	1	300
2017-03-27T15:13:25	21.5	23	7.32	1.3	240	52	23	7.32	1	240	35	23	7.32	1	300	14.5	23	7.32	1	240	63	23	7.32	1	300
2017-03-27T15:13:53	21.5	24	7.83	1.2	240	53.5	24	7.83	1	240	36	24	7.83	1	300	15.5	24	7.83	1	300	65	24	7.83	1	300
2017-03-27T15:14:21	21.5	24	7.83	1.2	180	53.5	24	7.83	1	240	36	24	7.83	1	300	15.5	24	7.83	1	180	65	24	7.83	1	300
2017-03-27T15:14:50	26	24	7.83	1.5	300	53.5	24	7.83	1	180	43	24	7.83	1	300	20	24	7.83	1	300	65	24	7.83	1	240
2017-03-27T15:15:18	26	24	7.83	1.5	240	53.5	24	7.83	1	180	43	24	7.83	1	300	20	24	7.83	1	240	65	24	7.83	1	180
2017-03-27T15:15:48	25	23	7.32	1.5	240	52	23	7.32	1	180	41.5	23	7.32	1	300	19.5	23	7.32	1	240	63	23	7.32	1	180
2017-03-27T15:16:16	25	23	7.32	1.5	120	52	23	7.32	1	120	41.5	23	7.32	1	240	19.5	23	7.32	1	120	63	23	7.32	1	120
2017-03-27T15:16:45	25	23	7.32	1.5	120	52	23	7.32	1	240	41.5	23	7.32	1	240	19.5	23	7.32	1	120	63	23	7.32	1	300
2017-03-27T15:17:14	21.5	23	7.32	1.3	120	52	23	7.32	1	180	35	23	7.32	1	240	14.5	23	7.32	1	120	63.5	23	7.32	1	180
2017-03-27T15:17:43	21.5	23	7.32	1.3	120	51.5	23	7.32	1	120	35	23	7.32	1	240	14.5	23	7.32	1	120	63	23	7.32	1	120

Figure 2: Note that only UberX surge factors were calculated using UberX rates and fees for the reasons discussed earlier in the paper.